INTERPRETING FOREST BIOME PRODUCTIVITY AND COVER UTILIZING NESTED SCALES OF IMAGE RESOLUTION AND BIOGEOGRAPHICAL ANALYSIS

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by

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GUIDE TO READING THE REPORT

The reader is encouraged to consult the Table of Contents in order to maximize efficiency in reading this report. The Executive Summary (I) summarizes key results from this effort and should be considered a road map for determining areas of interest. The Introduction (II) outlines the basis and background for the study. There is then division into two major components: productivity/cover estimation at TM and AVHRR scales of resolution (III and IV), followed by classification enhancement using TM and biogeographical data (V and VI). Each has a section devoted to methods and another to results and discussion. Special attention is recommended for the TM-AVHRR Scale-up sections (III.D and IV.B) since they describe much of the truly unique efforts in this project. The Overall Conclusions section (VII) reiterates some of the main points of the study in the context of future needs. The Bibliography (VIII) and Acknowledgements and Collaboration (IX) sections follow. Finally, the Appendix (X) consists of information on other extensive sites which underwent only preliminary investigations (A), a short description of the facilities and equipment used in the project (B), a summary of papers and presentations resulting from the study (C), and attached manuscripts and abstracts resulting from the study (D).

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I. EXECUTIVE SUMMARY

Many pressing environmental issues such as climate change and acid precipitation are global or regional in nature. Resolving these issues has been difficult in part because of their enormous geographic scale in relation to ground-based measures. Satellite imagery is the only source of extensive, synoptic data on global physical and biological features; however, not all features of the biosphere can be measured directly. Some must be modeled with process models that require spatially extensive estimates of driving variables and parameter values. In many cases, satellite sensors cannot measure even these variables and parameters directly. The dilemma of developing spatially extensive estimates of variables for which one only has local, ground-based, point estimates is unavoidable.

One approach to solving this dilemma is to make use of an underlying functional relationship between a secondary variable, measured by a satellite sensor, and the variable of interest to develop a model that predicts the desired information on the basis of the sensor data values. This approach depends on the existence of (1) a functional relationship between some sensor variable and the variable of interest and (2) ground-based data on the variable of interest that can be paired with sensor data to develop the model parameters. These models may be developed by regression or classification techniques. Examples of biological variables that have been related to satellite data in this manner are leaf-area index (Running et al., 1986), vegetation cover (e.g., Hopkins et al, 1988), and absorbed photosynthetic radiation (Asrar et al, 1984). By applying the models to full scenes of reflectance data, one can make spatially extensive estimates of the variables. In taking this approach one must consider:

1. The statistical properties of models that link ground-based values of a variable to satellite-sensed surface reflectance characteristics.
2. Whether models that use fine-scale spectral imagery to make predictions can be extended to larger regions by nesting fine- and coarse-scale imagery such as TM and AVHRR scenes.
3. How landscape heterogeneity and structure influence the observed relationship between the imagery and the ground-based data.

The objective of our research was to relate spectral imagery of varying resolution with ground-based data on forest productivity and cover, and to create models to predict regional estimates of forest productivity and cover with a quantifiable degree of accuracy. We took a three-stage approach, outlined in Figure 1. In the first stage, we developed models relating forest cover or productivity to TM surface reflectance values (TM/FOREST models). We were successful in making this TM/ground-based data link over four widely differing landscapes--southern Illinois, the Great Smoky Mountains in Tennessee, the Adirondack Mountains in New York, and the subalpine zone of the Colorado Rocky Mountains. In all cases the models were based on functional relationships between forest cover and forest productivity and landscape properties, phenology, and canopy characteristics that affected TM-measured surface reflectance characteristics. The TM/FOREST models were more accurate when biogeographic information regarding the landscape was either (1) used to stratify the landscape into more homogeneous units or (2) incorporated directly into the TM/FOREST model.

The statistical properties of the TM/FOREST models were sufficient to predict the mean or median forest productivity or cover of the landscape with a quantifiable degree of accuracy (standard error of the

estimate was $\pm$ 5 percent in some landscapes). The fine-scale (pixel-to-pixel) pattern of productivity was not well captured by these models, as the standard error about any single pixel prediction of forest productivity was greater than 30 percent. This results from heterogeneity of forests even at the TM scale, which created a large degree of unexplained variance despite the fact that the parameters of the model were well estimated [e.g., the models were highly significant ($p=<0.0001$), but r^2 values were low]. The error term for the average of all pixels in a landscape is dominated by the error associated with the parameters. The standard error about the expected value of a single pixel is dominated by the unexplained variance. Consequently, the TM imagery could be used successfully to estimate the productivity and cover of a landscape but not the pixel-to-pixel pattern of that productivity.

In the second stage, we developed AVHRR/FOREST models that predicted forest cover and productivity on the basis of AVHRR band values. AVHRR/FOREST models for the midwestern and southeastern regions of the United States were developed by overlaying a partial TM scene, previously used to generate landscape TM/FOREST models, with an AVHRR scene and subsequently relating AVHRR band values to TM-predicted forest cover or productivity (Fig. 8). These AVHRR/FOREST models had statistical properties similar to or better than those of the TM/FOREST models. The predicted forest cover value for an AVHRR scene encompassing Tennessee, Georgia, Kentucky, North Carolina, and Virginia had a standard error of $\pm$ 4 percent. Furthermore, the AVHRR/FOREST models explained more of the pixel-to-pixel variance; consequently, the models could be used to capture some of the broad-scale patterns of forest cover and productivity.

In the third stage, we compared our regional predictions with independent U.S. Forest Service (USFS) data. To do this we first created

regional forest cover and forest productivity maps using AVHRR scenes and our AVHRR/FOREST models. From these maps we calculated county values of forest productivity and cover. These image-derived county-level estimates of forest cover and productivity were then compared with USFS county-level values of forest cover and productivity. In all Illinois-region cases our forest cover estimates correlated well with those of the USFS (e.g., a correlation of 0.97 for forest cover of 77 counties in Missouri, a correlation of 0.87 overall for a 10-state midwestern region composed of 432 counties). Our forest productivity estimates also correlated well in the Illinois region with the USFS estimates (e.g., a correlation of 0.72 over all counties, and a correlation of >0.85 for counties within 200 km of the calibration site). In addition, the overall estimates of mean county percent forest and mean county annual growth were very close to that of the USFS estimates for the region (e.g., 24.2 percent for AVHRR vs. 21.6 percent for USFS estimates of percent forest, 39,300 cubic meters per county for AVHRR vs. 43,000 for USFS estimates of growth). Correlations and predictions were not nearly as good in the Smoky Mountain region, but the two estimates were highly and significantly correlated. Such results are a strong confirmation of the ability of our approach to develop regional estimates of variables for which there are only limited ground-based data and no direct means of measurement by satellite sensors.

It is apparent that the landscape has a strong influence on the success of our approach. We were most successful in the Midwest, where forests are uniformly dominated by hardwoods, topography is fairly consistent, and bodies of water are not an overwhelming feature of the landscape. These three features allowed consistent across-region interpretation of the TM and AVHRR spectral imagery. In the Southeast, forests are mixtures of hardwood and conifer stands, topography ranges

from the mountainous region of the Great Smoky Mountains to flatlands of western Tennessee, and bodies of water, while frequent, are also large. Our AVHRR-based predictions were relatively poorer under these conditions. Topography and conifer presence were influential because the AVHRR/FOREST models for the Southeast were derived from the TM/FOREST models which had been developed from ground-based data on hardwood forests in the Tennessee Smoky Mountains. The TM-forest productivity model was based in part on elevational temperature differences that were both captured by the TM sensor and strongly correlated with productivity in that particular landscape. In the Rocky Mountains the spatial pattern of the alpine and subalpine vegetation was too fine to be captured even with TM data, but was separated with the addition of biogeographical data such as slope, aspect, and elevation. However, the four montane forest ecosystems were not readily distinguishable with the available information. We therefore made no attempt to create AVHRR/FOREST models in this region because the fine-scale spatial heterogeneity precluded use of that approach and productivity data were unavailable. In the Northeast, we were less successful in developing TM/FOREST models than in either the Midwest or the Southeast, and preliminary efforts to develop AVHRR/FOREST models were unsuccessful. This is apparently a consequence of two factors: (1) the presence of many mixed hardwood-conifer stands and (2) the presence of many small wetlands and lakes. We were successful in developing TM/FOREST models only when we stratified the data based on forest type. In the larger AVHRR pixels, the forest/band value relationship was confounded by the extreme heterogeneity of the landscape, and we were unsuccessful in deriving a significant relationship.

In summary, an approach of using nested scales of imagery in conjunction with ground-based data can be successful in generating

regional estimates of variables that are functionally related to some variable a sensor can detect. Furthermore, this approach permits the error associated with such estimates to be documented. The approach will be most useful in regions in which either (1) the functional relationship is not confounded by other features of the landscape or (2) confounding landscape features can be stratified to reduce the overall variance. As new sensors are developed, more biosphere variables will be functionally related to satellite measurements. Our ability to detect global processes and map global patterns will depend on our ability to capitalize on these relationships.

II. INTRODUCTION

Many pressing environmental issues such as climate change and acid precipitation are global or regional in nature. Resolving these issues has been difficult in part because of their enormous geographic scale in relation to ground-based measures. Satellite imagery is the only source of extensive, synoptic data on global physical and biological features. Satellite sensors can directly measure many of the significant features which define and regulate the habitability of the globe; however, not all features of the biosphere can be measured directly. Some must be modeled with process models driven by physical and biological variables. The utility of these models for making regional or global predictions will depend in part on acquiring spatially extensive estimates of driving variables and parameter values. In many cases these variables and parameters will be difficult if not impossible to measure directly from data collected by the satellite sensors. The dilemma of developing spatially extensive estimates of variables for which one only has local, ground-based, point estimates is unavoidable.

One approach to solving this dilemma is to make use of an underlying functional relationship between a secondary variable, measured by a satellite sensor, and the variable of interest to develop a model that predicts the desired information on the basis of the satellite sensor data. This approach depends on the existence of (1) some functional relationship between some sensor variable and the target variable and (2) ground-based data on the variable of interest that can be paired with sensor data to develop the model parameters. These models may be developed by regression or classification techniques. Examples of biological variables that have been related to spectral data in this manner are leaf area index (Running et al., 1986), vegetation cover types

(Hopkins *et al*., 1988), and absorbed photosynthetic radiation (Asrar *et al*, 1984). In each of these cases the sensor was incapable of directly measuring the variable but measured a surface reflectance characteristic that was directly related to the target variable. By applying the models to full scenes of reflectance data, one can make spatially extensive estimates of the variables.

In making this linkage of spectral imagery and ground-based data, one must consider:

1. The statistical properties of models that link ground-based values of a variable to satellite-sensed surface reflectance characteristics.
2. Whether models that use fine-scale spectral imagery can be extended to larger regions by nesting fine- and coarse-scale imagery such as TM and AVHRR scenes.
3. How landscape heterogeneity and structure influence the observed relationship between the imagery and the ground-based data.

These issues will become increasingly significant as we attempt to measure global patterns and processes. The success of the Earth Observing System (EOS) and its moderate and high resolution imaging spectrometers (MORIS and HIRIS) will depend in part on our ability to use satellite imagery to extend local, ground-based data to larger regions.

It is well known that current satellite technology can be successfully used for a large number of ecologically meaningful analyses over relatively small areas. Innumerable examples exist for using such data to map and quantify vegetation on the landscape. Patterns of land-cover change over time have been assessed with multi-temporal data (Colwell, 1980; Hoffer. 1984; Woodwell *et al*., 1984; Hall *et al*., 1987;

Iverson and Risser, 1987; Sader and Joyce, 1988). Use of satellite data for determination of some functional attributes of communities, ecosystems, landscapes, and regions is now becoming increasingly important with investigators and funding agencies. For example, satellite data are being successfully used in assessments of vegetation stress due to disease, insect damage, drought, and pollution (Jackson, 1986; Rock et al., 1986; Vogelmann and Rock, 1986; Williams and Nelson, 1986). Vegetation productivity or biomass estimates have been made for several different ecosystems with a variety of sensors (Tucker, 1980; Lulla, 1981).

Most of these studies have been with agronomic crops (Idso et al., 1977; Gardner et al., 1982; Conese et al., 1986; Redelfs et al., 1987), grasslands (Pearson et al., 1976; Olang, 1983), wetlands (Butera et al. 1984; Hardisky et al., 1984), or shrublands (Vinogradov, 1977; Strong et al., 1985; Pech et al., 1986), and coniferous forests or plantations (Butera, 1985; Fox et al., 1985; Jensen and Hodgson, 1985; Franklin, 1986; Peterson et al., 1986; Running et al., 1986; Peterson et al., 1987; Wu and Sader, 1987). These studies reported varying degrees of success, with the relationships generally poorer as the system in question became structurally and functionally more complex (i.e., uneven-age forest systems have less reliable predictions of productivity or biomass than do most agronomic systems). Additionally, very little work has been reported for estimating forest productivity in deciduous-dominated forests, and none of these studies attempt to extend the relationships over large regions.

Advanced Very High Resolution Radiometer (AVHRR) data have been reported as very useful in monitoring gross correlates to primary productivity at the continental scale (Goward et al., 1985, 1987; Tucker

et al., 1985, 1986; Shimoda et al., 1986; Townshend and Justice, 1986). The normalized difference vegetation index (NDVI), when integrated over a growing season, has been highly correlated with preliminarily estimated net primary productivity of 24 North and South American biomes (Goward et al., 1987). Sadowski and Westover (1986) also used AVHRR data successfully as an estimator for rangeland greenness in monitoring grassland fire-danger hazard in Nebraska. It is generally difficult, however, to obtain ecologically valid estimates of primary productivity or other ecological parameters across an AVHRR scene directly since it is logistically difficult to obtain ground observations over such large regions for comparison to AVHRR remote-sensed information (Curran and Williamson, 1986).

One approach in estimating continental land cover has been to use multilevel sampling procedures with Landsat MSS data; this method carries potential although considerable numbers of scenes would need analysis to reduce standard errors of the estimates (Nelson et al., 1987). The combination of AVHRR and Landsat data provides another mechanism to calibrate ecologically meaningful information on the ground over vast areas. Conifer biomass modeling over large areas has been accomplished with some degree of success with the combination of MSS and AVHRR data (Logan, 1983; Logan and Strahler, 1983); the merger of TM and AVHRR for ecological purposes has not, to our knowledge, been reported.

Understanding and estimating the spatial pattern of forest cover and productivity at large scales is important for understanding biosphere processes. Forest covers an estimated 2.5 x 109 ha of the earth's surface (Southwick, 1985) and are a dominant feature of the global carbon and hydrological cycles (Moore, 1984; Southwick, 1985). Forests provide not only lumber, fuel, and paper for humanity, but also habitat for the

world's wildlife. The abundance and pattern of forests across a landscape can have significant effects on both wildlife and the economic well-being of a society.

Because of the size and longevity of trees, forest productivity is difficult to measure directly (Lieth and Whittaker, 1975); ground-based estimates of forest productivity tend to be localized and infrequent in many parts of the world (Olson, 1975; Goward et al, 1987). Consequently spatial patterns and absolute values of forest cover and productivity have been difficult to quantify at larger scales (Olson, 1975; Nelson and Holben, 1986; Nelson et al., 1987).

The objective of our research was to relate spectral imagery of varying resolution with ground-based data on forest productivity and cover to create models capable of predicting landscape and regional estimates of forest productivity and cover with a quantifiable degree of accuracy. Our strategy was to use satellite imagery to extend ground-based values of forest productivity and cover to landscape and regional estimates of cover and productivity. We took a three-stage approach (Fig. 1). The key questions which we addressed were:

1. Are there functional relationships between TM-observed surface reflectance characteristics and ground-based measures of forest cover and productivity that can be used to create TM-based models of forest cover and productivity (TM/FOREST models)? Can spatial differences in forest productivity be used in lieu of temporal differences in developing that model?
2. What are the statistical properties of such TM/FOREST models? How do their statistical properties control their utility?

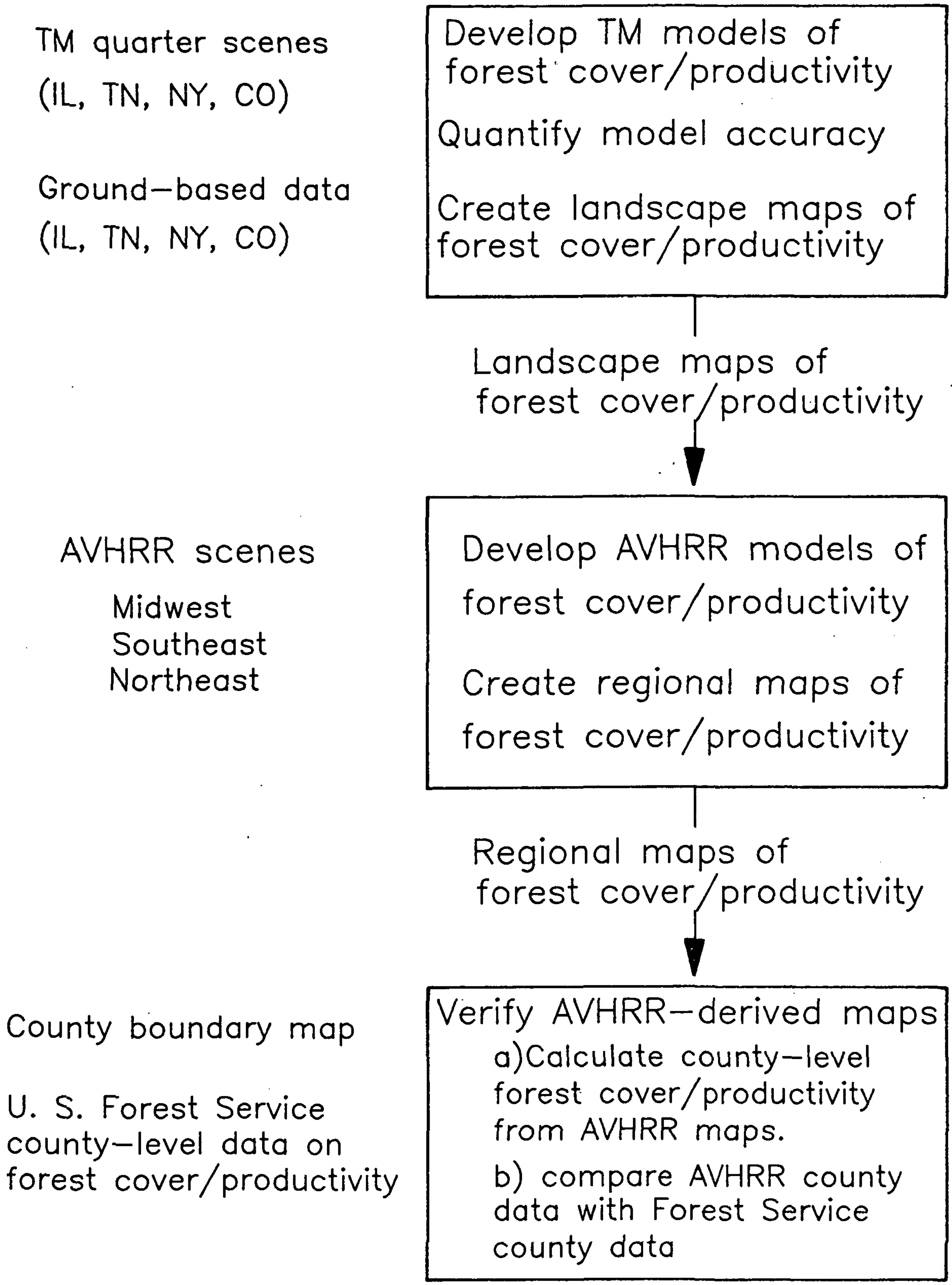

Fig. 1. Three-stage approach to ground-TM-AVHRR investigations reported in this study.

3. Can these TM/FOREST models be used in conjunction with nested TM and AVHRR imagery to develop coarse-scale AVHRR/FOREST models that are applicable to extensive regions?

4. Can such AVHRR/FOREST models be used in conjunction with AVHRR imagery to develop reliable regional maps of forest cover and productivity?

5. How does landscape heterogeneity and structure affect the utility of our approach for extending ground-based data?

In the first stage of our research, we examined the relationship of TM surface reflectance values and forest cover or productivity in four widely differing landscapes--southern Illinois, the Tennessee Smoky Mountains, the Adirondack Mountains of New York, and the alpine to montane zones of the Colorado Rocky Mountains. Ground-based data on forest cover and productivity were paired with TM spectral data of like resolution to develop models predicting forest cover or productivity from TM band values (TM/FOREST models). In the second stage, we paired AVHRR data with predictions of forest cover or productivity derived from TM/FOREST models to develop models predicting forest cover or productivity from AVHRR band values (AVHRR/FOREST models). In the third stage, we evaluated our multi-stage, multi-sensor approach for extending limited ground-based data by comparing regional predictions of forest cover and productivity generated with our AVHRR/FOREST models to independent USFS data.

In summary, our approach was to use nested scales of imagery in conjunction with ground-based data to generate quantifiably accurate landscape and regional estimates of two variables (forest cover and forest productivity), both of which cannot be directly measured by a sensor but

are functionally related to surface reflectance characteristics that TM and AVHRR sensors can detect.

III. PRODUCTIVITY/COVER ESTIMATION METHODS

A. Study Sites

1. Southern Illinois

The southern Illinois study area ranged from less than one county to about 10 states in size, depending on the component of the study (overall study area depicted in Figure 2). A TM-GIS (TM/FOREST) model for forest productivity was generated for the northern half of Pope County, Illinois. This area was also used as the calibration point for AVHRR productivity estimates (AVHRR/FOREST models). A nearby county, Jackson, was also the location for the calibration of AVHRR data for percent forests over a 10-state area centered on Illinois. A seven-county area in southern Illinois (including Pope and Jackson counties) was used for regression model building to compare mean forest production as estimated by the USFS to TM spectral signatures and ancillary GIS data.

The seven-county study area in southern Illinois averages about 36 percent forest cover and contains the Shawnee National Forest; it is the most densely forested portion of the state (Hahn, 1984). The area had over 95 percent forest prior to European colonization in the early 1800s (Iverson et al., 1986). These forests are part of the central hardwood zone of the eastern deciduous forests, and grow on a wide variety of sites.

Bottomland forests--primarily pin oak, cottonwood, maple and elm--exist in the major flood plains of the Mississippi and Ohio rivers and in the narrow valleys of smaller streams. Southern Illinois' bottomlands, about 100 m above sea level, are extremely fertile because of

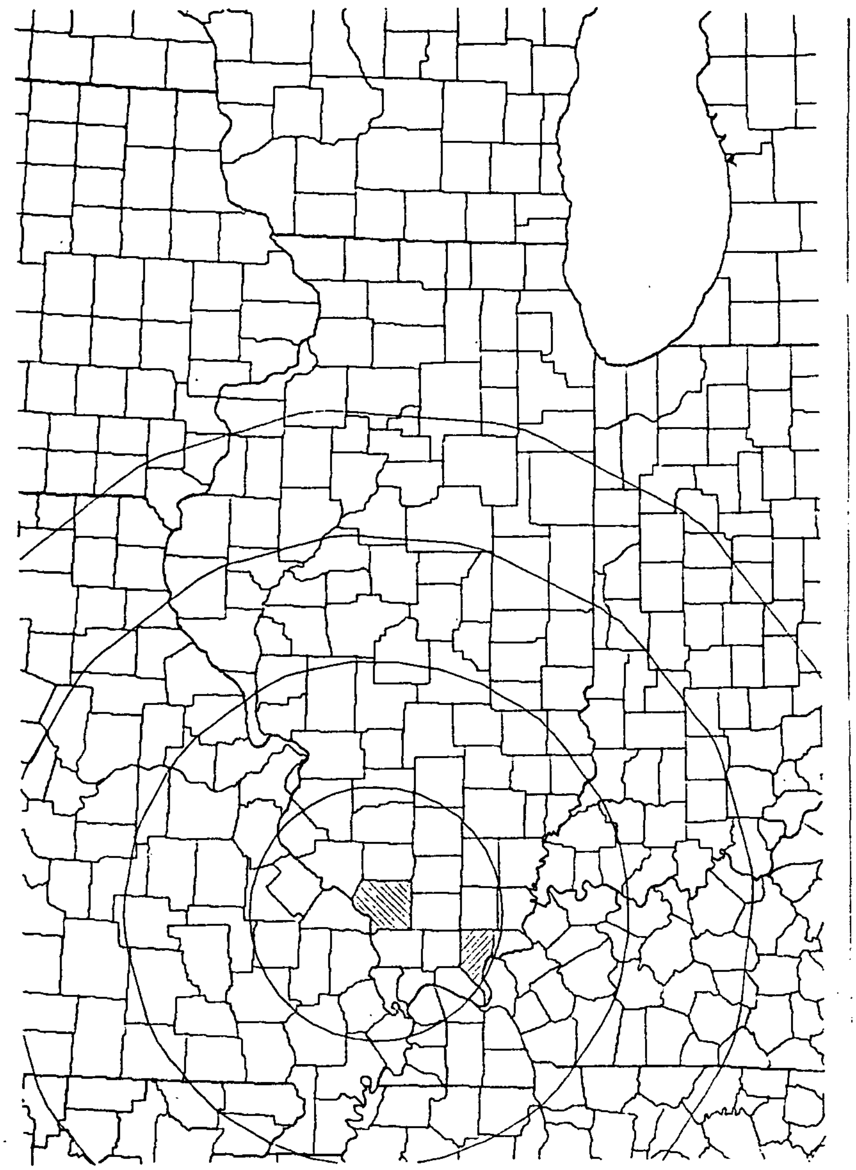

Fig. 2. Illinois region study area consisting of 10 states, 432 counties centered on Illinois. Also shown is the set of 100 km rings around the Jackson County calibration site.

continual deposition of new sediment from upslope and upstream erosion, but in some instances are restricted in productivity because of poorly drained soils.

The terrain of upland forest sites varies from level to steeply rolling, with deep loess to thin, rocky soils. In many areas of southern Illinois, forests persist only because steep slopes or soil conditions have limited agricultural use of the land. Most of the state's highest elevations occur here, but these reach only about 350 m above sea level such that elevation alone would not be expected to influence vegetation. Aspect and position does, however, influence the vegetation quality and quantity. Upland forests in the region are largely oak-hickory associations. There are small amounts of shortleaf pine plantations in the region, planted mostly on upland sites that were formerly agricultural fields abandoned in the 1930-1950 period.

The southern Illinois study area is cold in winter and hot in summer, with average daily temperatures of 2 and 25°C in January and July, respectively. Mean annual precipitation is about 1,060 mm, and is fairly uniformly distributed across the year. Winter precipitation generally results in sufficient accumulation of soil moisture, which minimizes summer drought on most soils (Herman, 1979). The average growing season length (days above 0°C) is 169 days, the period during which 55 percent of the annual precipitation falls.

2. Great Smoky Mountains

The TM/FOREST productivity analysis area in this region was located in the western portion of the Great Smoky Mountain National Park in Tennessee and North Carolina (Cades Cove 7.5 minute quadrangle) (Fig. 3). The area covers a complex set of ridges and valleys generally

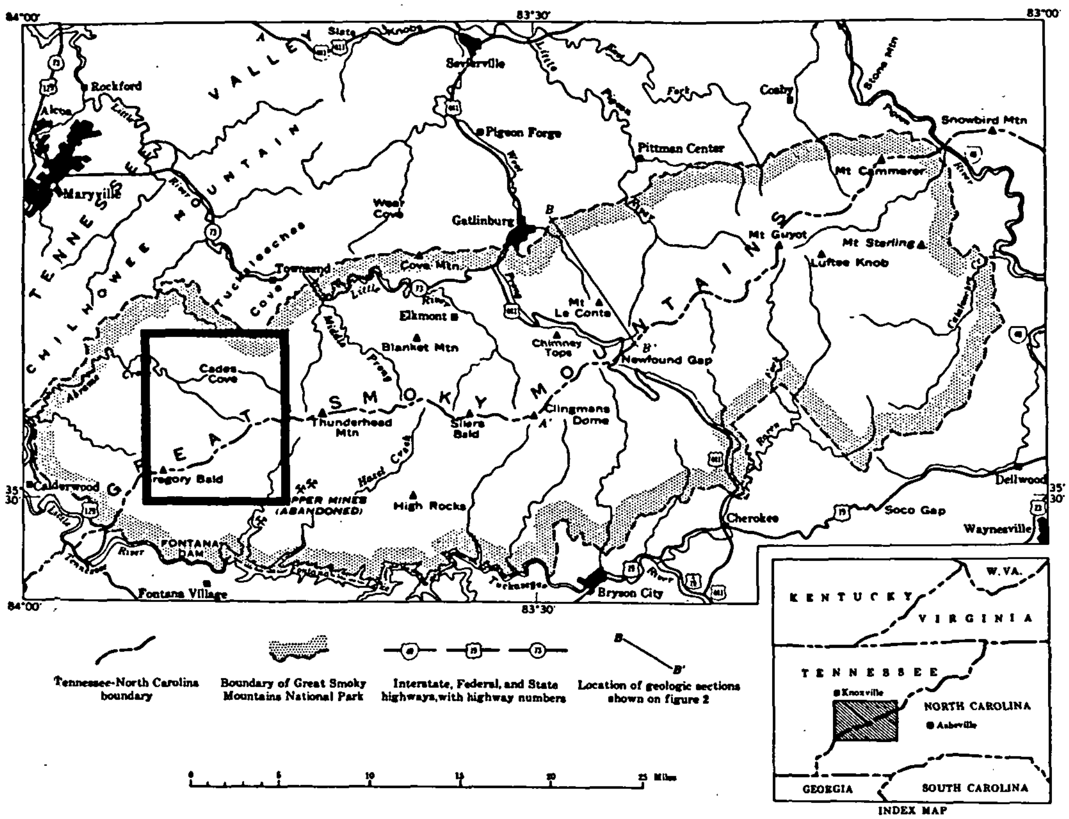

Fig. 3. Smokies region study area with the Cades Cove quadrangle as the intensive study site.

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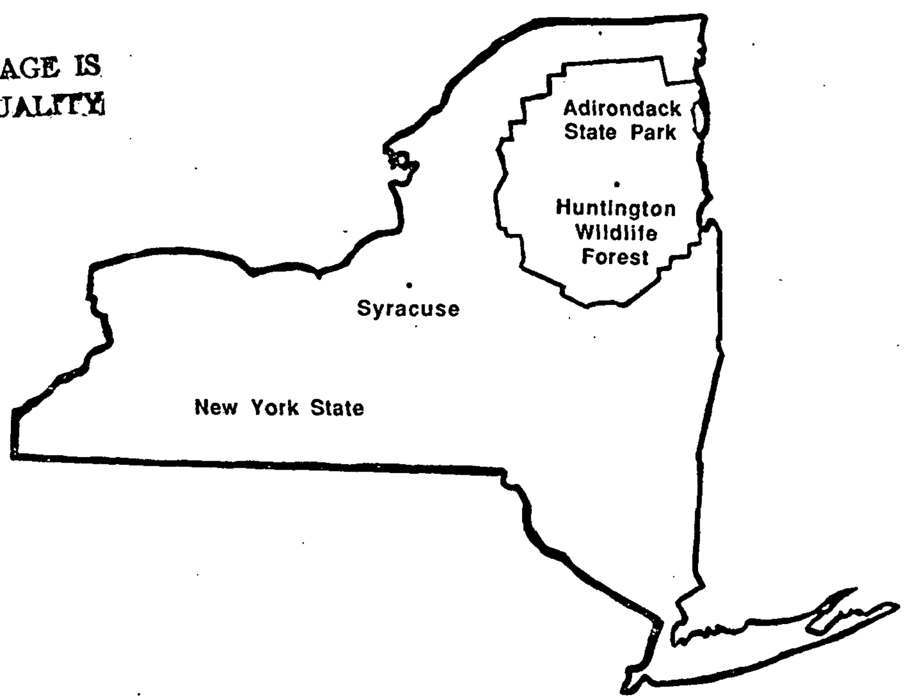

Fig. 4. New York's Adirondack Mountains study area with the Huntington Wildlife Forest as the intensive study site.

oriented in a north-south direction. Elevation ranges from 270 to 2024 m. Only 20 percent of the landscape is pristine. The other 80 percent has experienced direct human disturbance in the form of logging and farming, although these activities almost ceased 50+ years ago with the Park's establishment in 1934.

The climate in the Park is strongly influenced by the abrupt changes in elevation and the complex topography of the Great Smoky Mountains. Temperatures in February range from a monthly mean of 4.4°C at 445 m to -1.8°C at 1,919 m. July temperatures show a much more pronounced elevational difference, averaging 22.1°C at 445 m and 13.6 at the 1,919 m elevation. Precipitation increases with elevation. October is the driest month while February and March are the wettest.

The complex topography and extensive disturbance have created a finely patterned mosaic of vegetation communities. Successional forest covers much of the park. Cove forests containing 10 or more tree species occupy the sheltered mid-slope positions. On exposed low-to-middle elevation slopes, oaks, pines, black gum, sourwood, and red maple are found. Higher slopes have northern hardwood and hemlock communities, with spruce-fir at the highest elevations.

Regional extrapolation using AVHRR data encompassed portions of six states, from Kentucky in the northwest to Georgia in the southeast. The TM analysis for the Cades Cove area provided data for the scale-up approach with AVHRR.

3. Huntington Wildlife Forest, New York

The Huntington Wildlife Forest is managed as a research forest by the State University of New York (SUNY), College of Environmental Science and Forestry, Syracuse. The Forest is a 6,000-ha field station

located in the center of the Adirondack Mountains near Newcomb, New York (Fig. 4).

The vegetation of the Huntington Forest is transitional between the boreal forests to the north and the hardwood forests to the south. Of the 5,073 ha of forest, 3,409 ha are classified as northern hardwood (beech, sugar maple, yellow birch), 1,066 ha as hardwood-conifer (primarily red spruce and balsam fir with hardwoods), and 598 ha as conifer (white pine, white cedar, eastern hemlock). Elevations of the Forest range from 475 to 820 m above sea level. At the higher elevations, red spruce and balsam fir are the major species, whereas the hardwoods dominate the intermediate zones where soils are deeper and drainage is better. Eastern hemlock, red spruce, and balsam fir also occupy the poorly drained bottomlands around lakes and streams. The area was glacially scoured and has about 10 percent surface water.

The climate is cool and moist, with a mean annual temperature of 5.5°C (January -8.8°C, July 18.8°C). The average annual frost-free period is 122 days, with snowfall varying from 2,500 to 5,000 mm annually and snow cover continuous from early December to mid-April.

B. Data

1. Thematic Mapper (TM)

Thematic Mapper data were acquired for about 25 areas of the United States and Canada. Preliminary processing was done on many of these data while the project methodology evolved. As areas were selected for which the best combinations of all types of data were available, the following TM data sets covering these areas were processed extensively. A comprehensive listing of all project TM data was provided in earlier progress reports (Iverson _et al_., 1986a, 1986b, 1987).

These were the quarter scenes processed for southern Illinois:

Path	Row	Quad	Date of Coverage	Quality
23	34	2	7/18/84	Clear
		4		Clear
22	34	1	5/24/84	Clear
		3		Clear

These data covered two geographically disjunct portions of the Shawnee National Forest in southern Illinois, and in conjunction represented the seven-county region of the State studied in the TM-productivity analysis.

For the Great Smoky Mountains, the following scenes were processed:

Path	Row	Quad	Date of Coverage	Quality
19	35	4	9/8/84	Clear
19	35	4	10/26/84	Clouds 15%

These two quarter scenes provided multi-temporal coverage of the area surrounding Cades Cove quadrangle. The 9/8/84 quarter scene, because it was collected before significant senescence of the trees, was the more useful data set. although both scenes were processed.

At the Huntington Wildlife Forest in New York, two dates were observed:

Path	Row	Quad	Date of Coverage	Quality
14	29	3	6/17/84	Clouds 10%
14	29	3	9/21/84	Clouds 15%

In addition to these TM data sets for the Huntington Wildlife Forest analysis, the two scenes were normalized for solar irradiance to reduce between-scene variability (Markham and Barker, 1986). The calibrated data sets were merged by means of ratioing like bands from each date. The multi-temporal ratios were combined with the original data from both dates to generate a third TM data set.

2. Advanced Very High Resolution Radiometer (AVHRR)

AVHRR data used in the study were acquired from two sources. Initially, the data were available only from Satellite Data Services Division of NOAA. The data purchased from NOAA were HRPT format and required georeferencing in order for them to be useful in the methodology of this study. Difficulties were encountered in the transforming the data to UTM coordinates with a linear transformation algorithm, especially due to off-nadir distortions. At about that time in the project, EROS Data Center had perfected a georeferencing technique and were making geocoded AVHRR available to federal researchers. Therefore, geocoded AVHRR data of the Illinois, Great Smoky Mountains, and New York study areas were also acquired. The descriptions below mention which data were used for each area and the dates of coverage.

Geocoded AVHRR data collected 6/4/87, and covering all or some of Arkansas, Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Tennessee, and Wisconsin, were obtained from EROS Data Center for the Illinois region. The data has been referenced to the UTM coordinate system and resampled to a 1110 m x 1110 m pixel size. AVHRR Bands 1-4, visible to thermal range, were included in this data set.

For the Smoky Mountain region, HRPT format AVHRR data collected 9/28/85, and covering all or some of Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia, were purchased from NOAA. Four bands of information were included. Linear transformation to the UTM coordinate system was of acceptable accuracy, aided by the uniqueness of Cades Cove as an open area surrounded by a rather homogeneous forested landscape. Pixel size was 1,110 m x 1,110 m.

Geocoded AVHRR data collected 6/17/87 and covering the northeastern United States (including the Huntington Wildlife Forest), were obtained

from EROS Data Center. The data have been referenced to the UTM coordinate system and resampled to 1,110 m x 1,110 m pixels. Four spectral bands were also included in the data set.

3. Productivity

Fundamental to the TM-forest productivity analysis technique of this study was the availability of field data estimating forest productivity at a particular site. These data needed to be: (1) collected at a resolution similar to the TM data (30 m x 30 m), (2) measurements representative of the conditions "seen" by the satellite when the TM data were collected, and (3) identified in such a way that the exact locations of the plots (in UTM coordinates) were known or could be determined. Quality and number of these ground measurements varied by study area and are discussed below in more detail. We recognize that our productivity data are not estimates of entire ecosystem productivity, but only major components of that ecosystem production. For purposes of the discussion here, the term productivity is used even though we are only estimating a portion of the total ecosystem productivity.

An inventory of Illinois forest land was completed by the USFS in 1985. The data for 32 sample points from the inventory occurring in the study area were made available by the USFS for this study. Field plots varied in size according to land use patterns and tree size, but averaged 0.4 ha. Measurements taken at each site allowed for the calculation of mean annual increment (MAI) as an estimate of the main woody (above ground) part of total ecosystem productivity. MAI is defined in this case as the cubic volume of hardwood growing stock at a site divided by stand age (cu/A/yr). Volume and age of the plots were extrapolated from trees which had diameters in excess of 12.5 cm at breast height. Plot locations,

referenced to the nearest meter of UTM, were randomly selected to represent the conditions of forests in southern Illinois.

Forest productivity data for the Great Smoky Mountain study site were stand bole volume growth estimates taken from Callaway (1983). These data were developed from tree core measurements of 128 20 m x 50 m National Park Service permanent plots. The plots were selected to be representative of topographic range and degrees of disturbance in the Park. Plot elevations ranged from 523 m to 1,540 m. No spruce-fir stands were included. Each plot was divided into five subplots and a random sample tree was selected within each subplot. In order to represent the canopy species production exclusively, only trees with diameters greater than 30 cm at breast height (1.3 m) were chosen. Each sample tree was measured for diameter at breast height, bole height and 10-year radial growth increment. Bole volume growth (m^3/yr) was calculated as follows:

$$\text{Annual individual bole volume growth} = pi/3 \times H \times (r^2 - (r-I)^2)/10 \quad (1)$$

where r = radius at breast height (m),

H = bole height (m),

and I = 10-year radial growth increment (m)

Stand bole volume growth (m^3/ha/yr) was calculated by multiplying the average annual bole volume growth of the sample trees by 10X the number of trees greater than 30 cm diameter at breast height within the permanent plot. These data are very approximate estimates of bole volume growth of these stands and should be viewed really as indexes of forest productivity rather than actual forest productivity. However, the large sample size and diversity of site situations represented by the plots made the data

set suitable to this methodology even though important components of total ecosystem production are missing (Olson, 1971; Graham et al., 1988.

Continuous forest inventory plots were established in 1970 at Huntington Wildlife Forest by the SUNY Department of Environmental Science and Forestry at Syracuse. Remeasurements of the plots were taken in 1976 and 1981. Data from 173 of these plots were available for the TM analysis. Using the repeated measurements of tree diameter, coupled with published biomass regression equations for tree species found in the region, stand productivity at each site was clculated as change in live above-ground biomass plus mortality (kg/ha/yr). This measure of productivity in biomass was used as an index of forest productivity.

4. Biogeographical

Biogeographical data included any ecological attributes of the landscape available for a study site that were considered to be potentially important either as an independent variable used for explaining variability in forest productivity, or as a stratification variable for generating more homogeneous samples in TM and productivity data being analyzed. When possible, data were acquired in digital format. The quality and types of biogeographical data available varied by study site and are described below.

a. High Resolution

The Illinois study site was in part selected because of high quality, high resolution data available from the Illinois GIS, including landscape position, soil associations, slope angle and aspect, and vegetation community types. These were rasterized, reformatted, and

directly integrated with the TM and productivity data with image processing/GIS software.

Additionally, site information data were collected for each inventory plot by the USFS. Moisture class (xeric, mesic, hydromesic, or hydric) and slope angle, aspect, and position (one of the four quarters of the slope face) were incorporated with the other data. Woodland productivity indexes were translated from the Soil Conservation Service's ratings of soil mapping units on their ability to produce timber (Fehrenbacher et al., 1978); sun radiance indexes were calculated from aspect, slope angle, and latitude (Frank and Lee, 1966).

Callaway (1983) had documented elevation, aspect, slope, topographic position, soil depth, forest type, distance to nearest stream, and disturbance history of each plot location during his field work, and these were included in the TM-productivity analysis for the Smoky Mountain study area. A digital elevation model for the Cades Cove quadrangle was also used to project modeling results in three dimensions for better assessment of roles played by elevation and aspect in effecting forest production.

Soil mapping units for Huntington Wildlife Forest were digitized, and from these soil capacity for timber production was interpreted (sugar maple site index). Slope angle and aspect were known for each inventory plot, as was forest community type. Sun radiance indexes were calculated from slope angle, aspect, and latitude data.

b. Coarse Resolution

The Oak Ridge National Laboratory Geoecology data base (Olson, 1980) was used for verification of the AVHRR regional scale-up work (Section III D). The data set is a compilation of published data from the USFS ranging in age from 1965 to 1980, and contains data on

percent forest cover and annual growing stock growth at county resolution. The Illinois data in the Geoecology data base predated the most recent figures published after the inventory of 1985 (Hahn, 1987). These updated estimates were also included in the regional AVHRR analysis.

For the Smoky Mountain region, estimates of percent forest and forest production for 187 counties under jurisdiction of the Tennessee Valley Authority (TVA) were incorporated with the Geoecology data and tested. The TVA data were considered an improvement over the Geoecology information. largely because TVA included non-commercial forest lands in their estimates.

C. TM Productivity Analysis

Several methods were used to analyze the utility of TM data in explaining the variance in forest productivity. Regardless of the technique or study area, similar preprocessing steps were necessary in order to merge the TM and productivity data. An image processing algorithm was written that created a GIS output file identifying the pixels pertaining to ground sample points when given the UTM coordinates of their locations. By overlaying the two files, the GIS file was used to extract a 3 x 3 window of TM pixels surrounding the ground sample point and combine these data in an ASCII file for subsequent processing by SAS statistical analysis software. The reasons for using a 3 x 3 window of TM pixels were to allow for registration errors in both data sets and to take into consideration that the ground plots were larger than a TM pixel. Other biogeographical data were mostly collected with the productivity information and could therefore be merged into the ASCII files using the plot identification. Exceptions were noted above in the descriptions of biogeographical data by study area.

1. Correlation

a. Southern Illinois

Correlations were run between the estimate of forest productivity in cu ft/A/yr (MAI) and the variables listed in Table 1.

Table 1. Variables correlated with forest productivity estimates and used as independent variables in regression analyses for Illinois. Non-numeric biogeographical data were ranked as to expected effect on productivity.

1. All single band values (9 pixel averages)
2. All possible band ratios (9 pixel averages)
3. Transformed vegetation indexes (Tucker, 1979) (9 pixel averages)

    a. (Band4 - Band2)/(Band4 + Band2)
    b. (Band4 - Band3)/(Band4 + Band3)
    c. (Band5 - Band2)/(Band5 + Band2)
    d. (Band5 - Band3)/(Band5 + Band3)

4. Site moisture (xeric, xeromesic, mesic, hydromesic, and hydric)
5. Slope angle (percent)
6. Slope position (quarters of the slope face)
7. Aspect
8. Soil woodland productivity indexes
9. Sun radiance indexes

b. Great Smoky Mountains

Correlation analyses were performed with forest plot volume growth (cu m/ha/yr) or its natural log and TM and biogeographical values associated with the plots. The TM variables that were investigated are listed in Table 2. In all cases the mean TM value of the 3 x 3 pixel window associated with each forest plot location was used. Principle component values for pixels were generated by applying the ERDAS principal components program (PRINC) to the September TM scene. Because conifer canopies have very different reflective properties than hardwood canopies and thus confound the TM relationships, the plots were also stratified

into hardwood, conifer, and mixed community types to test for improvements in the correlations.

Table 2. Variables correlated with forest productivity estimates and used as independent variables in regression analyses for the Great Smoky Mountains.

1. All single band values (9 pixel averages)
2. All possible band ratios (9 pixel averages)
3. 4 TM vegetation indexes (9 pixel averages)

    (Band4 - Band4)/(Band4 + Band2)
    (Band4 - Band3)/(Band4 + Band3)
    (Band5 - Band2)/(Band5 + Band2)
    (Band5 - Band3)/(Band5 + Band3)

4. TM principal component values 1-7 (9 pixel averages)
5. Plot elevation (m)
6. Plot slope (percent)
7. Plot distance to stream (m)
8. Plot drainage - hectares of watershed above plot

c. Huntington Wildlife Forest, New York

Correlations were run between TM values, biogeographical data, and estimates of forest productivity (kg/ha/yr) for the 173 continuous forest inventory plots of the Huntington Wildlife Forest. The TM and biogeographical data used are listed in Table 3.

Table 3. Variables correlated with estimates of forest productivity, and used as independent variables in regression analyses for the New York site.

1. All single band values (9 pixel averages)
2. All possible band ratios (9 pixel averages)
3. 4 TM vegetation indexes (9 pixel averages)

    (Band4 - Band2)/(Band4 + Band2)
    (Band4 - Band3)/(Band4 + Band3)
    (Band5 - Band2)/(Band5 + Band2)
    (Band5 - Band3)/(Band5 + Band3)

4. Same band temporal band ratios (e.g. JuneTM3:SeptemberTM3)
5. Soil woodland productivity indexes
6. Sun radiance indexes
7. Slope angle (percent)

Stratified correlations were also run using aspect and community types as the strata. Using eight aspect directions resulted in sample sizes too small for some of the directions, so they were grouped into three general categories: E, SE, and S; N, NE, and NW; and W and SW. These were intended to represent the general aspect orientations known to effect plant communities. Forest community types are listed in Table 4.

Table 4. Community types of Huntington Wildlife Forest (New York) used for correlation and regression stratification.

1. White pine, white cedar
2. Beech
3. Red spruce, yellow birch, balsam fir, red maple, beech
4. Red maple, yellow birch
5. Sugar maple, beech, yellow birch
6. Sugar maple, beech

2. Regression Modeling

a. Southern Illinois

Multiple regression analysis was used to investigate which TM and biogeographical data best accounted for the variance in the forest productivity index. The method of multiple regression used was called R-SQUARE in SAS, which ranks the models from best to worst (by largest r^2) for all possible combinations of the independent variables being used. Diagnostics were also run to investigate problems of collinearity among the independent variables. Independent variables were weeded from the analysis if they were highly correlated with other independent variables that contributed more to the r^2 of the model. Ultimately a model was selected as "best" based on the highest adjusted r^2, significance of the model, a high probability that the parameter of

each variable in the model was non-zero, and that the model did not violate regression assumptions concerning collinearity. Variables investigated as independent variables for Illinois are listed above in Table 1. Once a model was selected, its mathematical formula was applied to each TM pixel of the Illinois region to generate a productivity map.

b. Great Smoky Mountains

All comments made above concerning regression analysis for the Illinois study site also pertain to the Smoky Mountains. Additionally, with the advantage of more sample points of productivity data, the Smoky Mountain regression analyses included stratification by forest associations of hardwood, mixed, and conifer. Independent variables are listed above in Table 2.

c. Huntington Wildlife Forest, New York

Variables used as independent variables in the regression analyses are listed in Table 3. Once again, techniques were similar to those discussed under Illinois. Regression was also performed with stratification by three aspect categories and six forest community types (Table 4).

3. Classification/ANOVA

a. Great Smoky Mountains

An unsupervised classifier was applied to the September TM scene to classify the pixels into 35 categories. Using topographic maps. some familiarity with the area, and mean band values for each of the 35 classes, the classes were identified as water, non-forest, or forest. The TM cover classes for the nine pixels (3 x 3 blocks) associated with

the point location of each forest productivity plot were written to an ASCII file for statistical analysis. Each plot was assigned to the class that occurred most frequently within the nine pixels (none was associated with non-forest or water). Only plots in which the most common class occurred in at least four of the nine pixels were used in subsequent statistical analyses. Of the 128 plot locations, only five plots had to be dropped for this reason. Another 12 plots were dropped because of insufficient sample plots within a class type, i.e., only one to four plots had that class type. The plot frequency distribution of six class types that were associated with at least six forest productivity plots was virtually identical to the frequency distribution of those classes within the entire classified scene.

Once each plot had been assigned to a class or dropped from the data set for the reasons above, analysis of variance was performed on the data in several ways. Both stand volume growth and the natural log of stand volume growth were used as dependent variables. An unbalanced 1-way analysis of variance was performed to determine if TM class type could explain a significant portion of the observed variation in forest productivity (ANOVA Model I). A covariate variable, plot elevation, was then introduced into the 1-way analysis (ANOVA Model II). In the third and fourth tests. pure pine plots were eliminated from the data set and a 1-way analysis of variance was performed with and without the covariate variable of elevation (ANOVA Models III and IV). The plots were also classed into four aspect classes (NE, SE, SW, and NW), and a 2-way analysis of variance using TM class and aspect as the independent variables was performed. Analysis of variance using plot elevation, plot slope, or plot distance to water as the dependent variable was also used to examine the relationship of class type to these features. Using results

from the analyses of variance, productivity values were assigned according to the classes for each forested pixel in the region to produce a productivity map of the region.

The October scene was also classified in the same manner as the September scene with the intention of performing the same analyses. However, once the class values for the nine pixels surrounding each plot location were extracted from the classified October scene, it became apparent that further analyses would be fruitless because (1) far fewer of the plots were associated with four or more pixels with the same TM class and (2) there were few TM classes which had six or more plots associated with them.

b. Huntington Wildlife Forest, New York

The June TM data for Huntington Wildlife Forest (Fig. 5) were classified into 30 classes using the unsupervised classifier, which were subsequently identified as water, non-forest, or forest. As described in the Great Smoky Mountain methodology, nine pixel blocks were given the class identification of the most commonly occurring class. At least six plots had to fall into a class for the class to be considered in the analysis. ANOVA analysis was run on the plots using all sites (n=144), as well as stratified according to forest cutting dates. It was assumed that if a highly productive site had been thinned before the TM data were collected, the relationship of TM values and productivity data would be confused. The six cutting stratifications were: (1) all sites not thinned after 1976 (n=116), (2) all sites thinned after 1976 (n=28), (3) all sites not thinned after 1970 (n=86), (4) all sites not thinned before but thinned after 1976 (n=24), (5) all sites thinned between 1970 and 1976 but not after 1976 (n=30), and (6) all sites thinned both between

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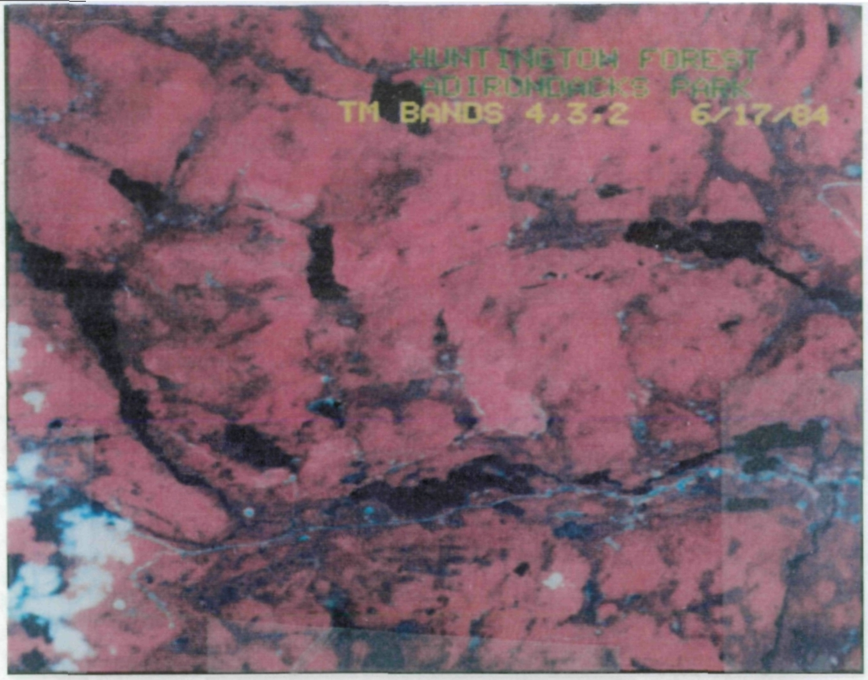

Fig. 5. Landsat TM for Huntington Wildlife Forest in the central Adirondacks.

Fig. 6. AVHRR raw data for Illinois study region.

Fig. 7. AVHRR raw data for Smokies study region.

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1970 and 1976 and between 1976 and 1981 (n=4). It should be noted that these cutting times were inferred from decreases in basal areas recorded at the sites. If the basal area decreased by 20 ft^2/plot or more the site was assumed to have been cut. The results of ANOVA for New York were inconclusive and will not be discussed in this report.

D. TM/AVHRR Scale-Up

1. TM/AVHRR Calibration

For southern Illinois and the Great Smoky Mountains, a procedure was developed to use the TM data as a vector for calibrating AVHRR pixels to estimate forest cover or productivity over large regions. An AVHRR data set covering 564,175 km^2 centered on Illinois (latitude 34-44 N, longitude 86-94 W) for June 4, 1987, was acquired from the EROS Data Center, Sioux Falls, South Dakota (Fig. 6). These data had been geocoded to Universal Transverse Mercatur (UTM) coordinates and resampled to 1,110 m x 1110 m. Similarly, AVHRR data for September 28, 1985, from a 243,090 km^2 area centered on the Smoky Mountains (latitude 33-37 N, longitude 81-86 W), were acquired from the National Oceanographic and Atmospheric Administration (NOAA) (Fig. 7). Georeferencing of these data to UTM coordinates was performed to subpixel accuracy, using a linear transformation algorithm generated from ground-control points (e.g., slopes and grassy balds) and adjusted via the known UTM's of prominent features in the AVHRR data such as Cades Cove.

The acquisition dates corresponded to time intervals when all forests in the study areas would be in full leaf stage, whereas the signatures from row-crop agriculture (the dominant non-forest feature of especially the Illinois region) would be dominated by non-chlorophytic plants since acquisition was early or late in the crop calendar years.

The AVHRR data were then overlayed with TM data for a portion (99-154 1,110 m x 1,110 m AVHRR pixels occupying 120-190 km^2) of the study areas, subset to cover precisely the same areas, and resampled to the TM's 30 m x 30 m pixel size which subdivided each original AVHRR pixel into 1,369 (37 x 37 matrix) pixels. These files were merged to create an 11-band file, including TM Bands 1-7 and AVHRR bands 1-4. Also added to these files were bands containing class assignments from an unsupervised classification of the TM data used to derive percent forest and productivity estimates, and an identification field, to group pixels according to each original AVHRR pixel for analysis. An additional band for the Illinois region contained productivity estimates for each pixel generated from the TM regression model for the region.

The resulting files are represented for one case, Cades Cove in the Smoky Mountains (Fig. 8) where the green gun corresponds to TM Band 4 data, and the red gun corresponds to AVHRR Band 2 data. A sampling program extracted data from this file from every fourth line and fourth column (a 1/16th sample) to reduce data density, and data were output to ASCII files for SAS statistical analysis. Correlation and regression analysis were used to test relationships between productivity or percent forest calculated from TM regression models or classifications for each original AVHRR pixel and various AVHRR spectral characteristics, including AVHRR Bands 1-4, the normalized difference vegetation index (Band2-Band1/Band2+Band1), band ratios, and various other indices which included Bands 3 and 4 and have been used previously for assessing agronomic species biomass (Gardner et al., 1982). For regression models, productivity or percent forest estimates as ascertained by TM data were used as independent variables with AVHRR spectral characteristics as the dependent variables.

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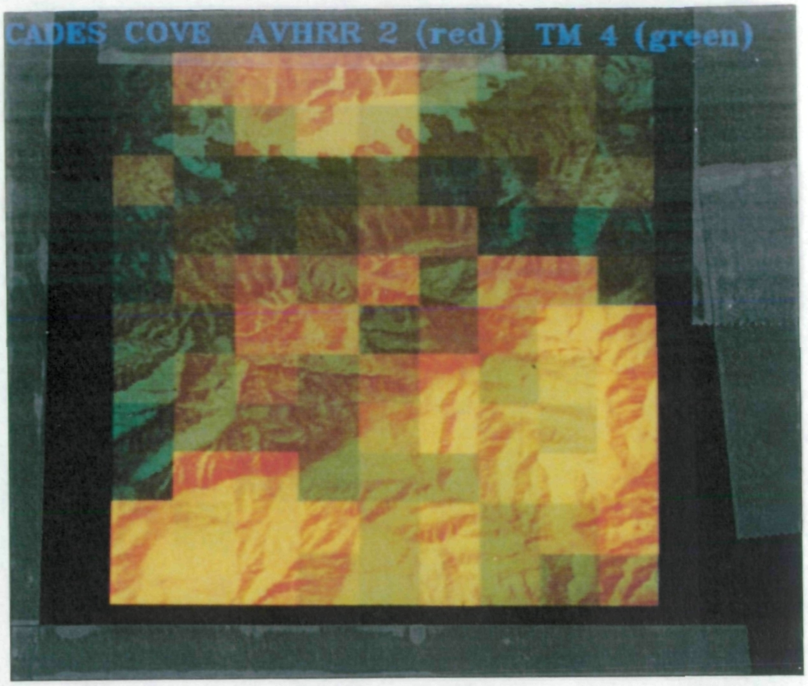

Fig. 8. TM - AVHRR overlay for Cades Cove Quadrangle, TN.

WHITTAKER'S (1952) REPRESENTATION OF VEGETATION TYPES ON AN ELEVATION AND MOISTURE GRADIENT

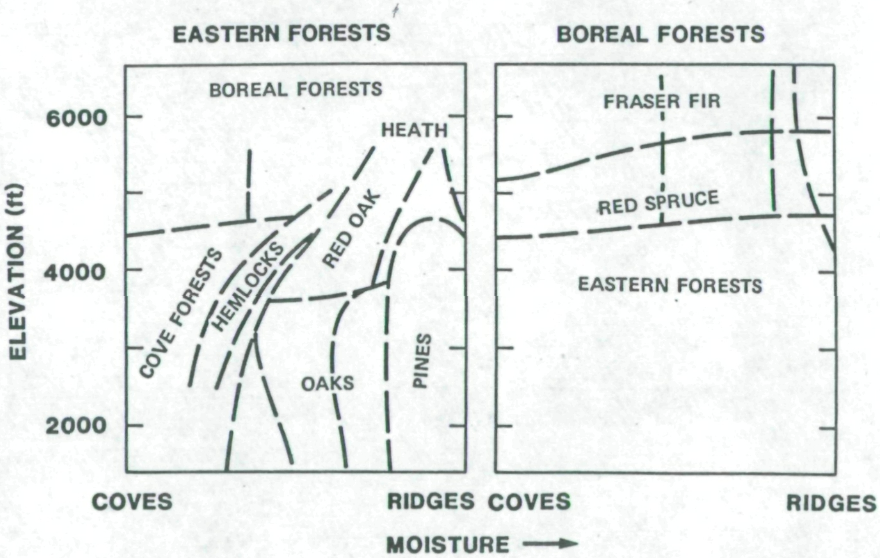

Fig. 9. Representation of vegetation types in the Smokies based on elevation and moisture gradients (after Whittaker 1952).

2. Percent Forest Estimation by County

The best AVHRR regression models which predicted percent forest were applied to the AVHRR data sets in the following manner. An unsupervised classification was performed on the 4 band AVHRR data to mask out water, bare ground, and other non-forest data. A very conservative approach was taken in assigning classes with the aid of maps and aerial photographs such that if the pixel was interpreted as having any forest, it was classed as a forested pixel. The regression equation was then applied to each AVHRR pixel to produce an estimate of percent forest over the entire region. From the resulting data set, a standard error around the mean and 95 percent confidence intervals were calculated to estimate the variance of the regression predictions. The percent forest estimates were then classified into seven cover classes to ease data manipulation and visual interpretation: 0 percent, 1-20 percent, 21-40 percent, 41-60 percent, 61-80 percent, 81-99 percent, and 100 percent.

To project AVHRR-estimated forest cover percentage over entire counties, the percent forest classified GIS layer described above was overlain with a GIS of county boundaries. A summary text file was then produced which gave the number of pixels of each class for each county; this file was imported into SAS for calculating forest cover for individual counties.

3. Productivity Estimation by County

A similar approach was used to estimate forest productivity over the study regions. In this case, a productivity map derived via regression analyses for northern Pope County was used as the calibration center to formulate the regression equation used over the Illinois AVHRR

scene, and the Cades Cove quadrangle classified into productivity classes was used for the Smoky Mountains region. Total growth estimates for each AVHRR pixel were made by summing the growth projected for the 1,369 TM pixels within an AVHRR pixel. Similarly, total county growth estimates were calculated by summing the estimates of growth for each AVHRR pixel within a county.

4. Verification of AVHRR Estimates

Once the output estimate of percent forest class or productivity over the entire AVHRR study area was produced via regression analysis, it was important to compare the output data against another data set. The USFS data, acquired by county nationwide, was selected as the validation data set, and was available through Oak Ridge National Laboratory's (ORNL) Geoecology data base (Olson, 1980). This data set is a compilation of USFS published data ranging in age from 1965 to 1980. An additional, more current data set was acquired for the Smoky Mountain region from the TVA. Because of the more current data and a better estimation of non-commercial forest land in the TVA data, they were chosen for use over the ORNL Geoecology data for the Smoky Mountains.

The county data were then merged to a vector GIS coverage of all U.S. states and counties by FIPS codes, rasterized to a grid cell size which matched that of the AVHRR data (1,110 m x 1,110 m), registered to UTM Zone 15 (Illinois) or Zone 16 (Smoky Mountains) projection, and subset to match the appropriate AVHRR data set. The two data sets (AVHRR and Geoecology or TVA) were then output to SAS for statistical comparisons between the estimates of cover or productivity. The data were also output to ERDAS for display of county estimates from AVHRR, Geoecology or TVA,

and difference maps depicting geographically where similarities and dissimilarities existed in the estimates.

Correlation analyses were performed to compare the AVHRR estimates to the Geoecology or TVA (USFS) estimates of percent forest or productivity. This was done in three ways: all counties grouped together, counties stratified by state, and counties stratified by distance from the calibration center. For the latter evaluation, ARC/INFO was used to create circular buffers away from the center point of the calibration area of 0-100, 100-200, 200-300, 300-400, and >400 km; the counties were then assigned a buffer code for stratification. A total of 432 counties existed in the Illinois study area scene, and 182 counties in the Smoky Mountains scene. If less than 75 percent of land area of a particular county existed in the AVHRR scene (edge counties) it was eliminated from statistical analysis. County means from the two estimates were also compared using pair-wise t-tests.

For two states, Illinois and Missouri, a second, more recent, source of data was used in addition to the Geoecology data. This was done to test the impact of using older data sets as well as data from a different source. For Illinois, 1985 USFS Inventory percent cover and annual growing stock growth data (Hahn, 1987) were substituted for the 1965 data. With Missouri, data used were a result of digitization of forests interpreted from 1984 TM photographic images (Giessman et al., 1986).

IV. PRODUCTIVITY/COVER ESTIMATION RESULTS AND DISCUSSION

A. TM Production

1. Correlation

a. Southern Illinois

Among the 32 forest plots considered in this analysis, mean annual increment (MAI) ranged from 0.6 to 5.5 cu m/ha/yr (8.7 to 78.7 cu ft/A/yr). The strongest correlation between MAI and TM spectral characteristics was with the ratio of Band 7 to Band 4 ($r=-0.46$, $p<0.01$). Few variables correlated with MAI significantly; only band ratio 7:4 and band ratio 7:1 correlated at the 0.01 level of significance, with eight other variables correlating at the 0.05 level (Table 5). Several of these could be significant on chance alone, so caution must be exercised in interpretation of these results.

However, a couple of points can be made based on individual correlation coefficients: (1) the spectral information clearly provides more information on forest productivity than do other single characteristics acting independently, such as slope, moisture class, sun radiance, and soil woodland productivity index. Spectral data are by nature integrators of a large number of factors, many of which (e.g., moisture, density, green leaf volume) could be expected to influence productivity more than other single landscape attributes and (2) ratioing of the raw TM data increases information content relative to single band data or even transformed vegetation indexes when considering forest productivity. Ratioing minimizes radiometric distortions across the imagery (Leckie, 1987) and reduces some topographic effects (Short, 1982). Ratioing also accentuates the effect of interacting components.

Table 5. Correlations between TM band values and plot forest productivity for Illinois. Correlations in which p=<0.05 are shown. If p=<0.01 then *.

July 18, 1985

TM Variable (all plots)	r (n=32)
Band7/Band4	-0.46*
Band7/Band1	-0.44*
Band7/Band5	-0.40
Band7	-0.39
Band5/Band4	-0.39
Band7/Band2	-0.38
Band7/Band3	-0.38
Band4/Band2	+0.37
Band7/Band6	-0.36
(Band4-Band2)/(Band4+Band2)	+0.35

The inverse correlation of MAI and band ratio 7:4 could be interpreted as an interactive effect of greater leaf-water and greater biomass on more productive sites. Band 7, in the middle infrared, is indirectly related to leaf-water content; Band 7 values are reduced on higher productivity sites because more leaf water is available to absorb in that spectral range (Badhwar et al., 1986). Band 7 alone is significantly correlated with MAI, which supports this assumption (Table 5). On the other hand, Band 4, in the near infrared, has been shown in some studies (though not this one) to be directly related to vegetation density or biomass (Knipling, 1970; Badhwar et al. 1984). Ratioing Bands 7 and 4 accentuated the differences to provide a relationship stronger than either single band. Most of the significant correlations had Band 7 as a component and can be interpreted similarly (Table 5).

None of the landscape attributes correlated significantly (p=<0.05) to MAI, although the soil woodland productivity index correlated at the 0.1 level of significance. County soil survey map resolution is not as fine as the forest plot and TM data such that unrecorded inclusions of

soil units too small to map or errors in boundary lines could account for the poor relationship (Soil Conservation Service, 1951).

b. Great Smoky Mountains

Natural log transformation of the productivity data increased the amount of data variance which could be explained by TM and/or biogeographical data using any method of analysis. Other researchers have reported that the sensitivity of TM bands to such forest variables as basal area and leaf biomass decreases with increasing basal area or leaf biomass and thus a logarithmic transformation of these variables improves the TM relationships (Franklin, 1986). It also helps to make variance more uniform so that regression and variance analysis assumptions are fulfilled.

The correlation analysis showed that (1) the same TM variables in both the September and October scenes were significantly correlated with forest productivity, (2) the TM bands were highly correlated with each other and with the biogeographical variables, (3) raw band data or band ratios were much better correlated with the forest productivity data than were TM vegetation indices or TM principle component values, and (4) TM variables were better correlated with the natural log of volume growth than just volume growth (Table 6).

The same set of TM variables tended to be correlated with productivity in both scenes (Table 6). The ability of these variables to account for a significant proportion of the variance in productivity is explained by (1) the influence of topography and phenology (timing of leaf senescence) on reflected or emitted radiation and (2) the relationship of forest productivity to topography and phenology. Forest productivity in the Smoky Mountains is related to both elevation (negative) and soil

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Table 6. Correlations between TM band values and plot forest productivity data by date of Smoky Mountain TM scene. Only correlations in which p<.01 are shown. If p<.001 then "**". If p<.0001 then "***". If variable is significant for both dates for all plots then "+". If a variable is significant for both dates for "hardwood" plots then "#". Hardwood plots are those plots containing hardwood trees.

September 8, 1985				October 26, 1985			
TM var. (all plots)	r (n=128)	TM var. (hrdwod.)	r (n=111)	TM var. (all plots)	r (n=112)	TM var. (hrdwod.)	r n=95
6/1	+.391***	#6/1	+.518***	7/3	-.369***	#7/2	-.427***
+6/3	+.382***	#6/3	+.421***	7/2	-.261***	#7/6	-.425***
6/2	+.359***	6/2	+.375***	+7/6	-.356***	#7	-.416***
+3/1	-.282	#3/2	-.350**	+7	-.350**	#7/1	-.410***
+7/6	-.259	#7/6	-.342**	+7/1	-.350**	#7/3	-.409***
+6/5	+.254	#6/5	+.323**	7/5	-.310	#3/2	-.400***
+3/2	-.251	#7	-.323**	+3/2	-.296	#6/3	+.378**
+7	-.229	#7/4	-.320**	+6/3	+.295	#3	-.373**
+7/1	-.227	#3/1	-.316**	(5-2)/5+2)	-.294	#3/1	-.357**
		#7/1	-.303*	5/2	-.293	#7/4	-.354**
		#5/4	-.299*	3	-.282	#7/5	-.349**
		#7/2	-.294	+6/5	+.279	5/2	-.349**
		#7/5	-.283	5	-.274	(5-2)/(5+2)	-.337**
		#3/	-.261	+3/1	-.273	#6/1	+.329
		#5/	-.255	5/1	-.272	#5	-.329
		6/	+.253	7/4	-.260	5/1	-.319
		#7/3	-.249	5/3	-.243	#6/5	+.315
						#5/4	-.309
						1	-.279

moisture (positive) (Whittaker, 1966). The soil moisture is also a function of topography as ridges are dry and coves are wet. Forest types occur in different locations in this matrix of elevation and moisture (Fig. 9). In a morning and mountainous-terrain scene, high values of Band 6 (thermal) will be found at the warmer, lower elevations. Indeed there was a strong negative correlation between Band 6 and elevation ($r=-0.804$ $p=<0.0001$). Since forest productivity is strongly linked to elevation, it follows that Band 6 should be positively related to productivity in this mountainous terrain. Also, hardwood canopies are generally warmer than conifer canopies and thus higher Band 6 values would be expected from the warmer, generally more productive hardwood stands. The relationship of forest productivity to Band 6 is, however, confounded by (1) sunny, warm, dry south-facing slopes that are low in productivity due to lack of soil moisture and (2) pine stands which are likely to be cooler when the canopy is more dense (e.g. more productive) (Franklin, 1986; Sader, 1986). Consequently dividing Band 6 by Bands 1, 2, or 3, which are sensitive to foliage biomass amount and quality (Tucker, 1979; Badhwar _et al._, 1984; Franklin, 1986) yields the best correlation with forest productivity. Phenology may explain why Band 1 was better than Bands 2 or 3 in early September. Absorption in Band 1 is related to both chlorophyll and carotenoids (Tucker, 1979). In early September, leaves were just starting to turn color. The expression of fall color is partly a reflection of the relative ratios of chlorophyll to carotenoids. The timing of fall color is a function of species, elevation (earlier the higher), and moisture (earlier the drier). Thus, at this time of year Band 1 may have been more sensitive to features related to productivity such as species, elevation, and moisture than the other two bands. This may also explain why the Band6:1 ratio was much more strongly correlated to forest

productivity if only hardwood or mixed pine hardwood stands were considered (r=0.518 (n=111) versus r=0.391 (n=128)). Bands 7 and 5, which were important explanatory variables in October, cover regions of the spectrum in which water is absorbing radiation (Tucker, 1979). As foliage senesces the canopy contains less and less water. Thus, Band 7 and Band 5 values should increase as the forest canopies turn color, lose leaves, and dry out. Since senescence occurs earlier at high elevation and on dry sites and those are the sites with low forest productivity, one would expect that Band 5 and Band 7 should be negatively correlated with forest productivity in fall TM scenes. Indeed, in comparing the September scene to the late October scene Bands 5 and 7 became increasingly significant (Table 6).

c. Huntington Wildlife Forest, New York

Because more forest productivity plots were available for the New York study area and because of the multi-temporal TM data, many iterations of correlations were run using stratifications and different TM data. In general, for each of the three TM data sets (June 17, 1984; September 21, 1984; and the merged data set of the two dates after calibration) correlations were generated for all plots, plots stratified by six forest community types, and plots stratified by three aspect directions. The significant correlations for these are listed in Tables 7 to 9.

A few general conclusions can be drawn from these tables: (1) the June TM values overall correlated more strongly with forest productivity, especially in the calibrated data set--one could assume that at this northern latitude, in late September, the trees have begun to senesce, thus reducing the characteristics such as chlorophyll and moisture content

Table 7. Correlations between TM band values and plot forest productivity data by date of New York TM scene. Only correlations in which p<.01 are shown. If p<.001 then **, p<.0001 then ***. If variable is significant for both dates then +.

TM var.	r	TM var.	r	TM var.	r
June 17, 1984		Sept. 21, 1984		Merged June/September	
(n = 161)		(n = 147)		(n = 144)	
+3/1	-.423***	3/2	+.357***	June 7/5	-.415***
2/1	-.396***	+3/1	+.272**	+June 3/1	-.385**
+3	-.377***	+6/3	-.227*	June 3/September 3	-.379***
2	-.371***	+(4-2)/(4+2)	+.209	June 7/4	-.379***
7/5	-.371***	6/4	-.205	June 3	+.377***
+6/3	-.316***	+3	+.202	June 2	-.368***
7/4	-.304***	+4/2	+.191	June 2/1	-.361***
6/2	+.287**	4/1	+.181	September 3/2	+.294***
6	-.244*	4	+.170	June 5/4	-.284**
+5/4	-.221*	+5/4	-.167	June 2/September 2	-.243
+(4-3)/(4+3)	+.206*			+September 3/1	+.240
4/3	+.200			June 7	-.238
+(4-2)/(4+2)	+.199			June (4-3)/(4+3)	+.236
+4/2	+.199			June 7/1	-.231
7	-.191			June 4/3	+.288
7/1	-.181			June 4/2	+.218
				June (4-2)/(4+2)	+.236

Table 8. Correlations between TM band values and plot forest productivity data for New York, from June, September, and merged TM scenes. Correlations are based on stratification of plots by community types. Only correlations in which $p<.01$ are shown. If $p<.001$ then **, $p<.0001$ then ***. If variable is significant for more than one community type, then #.

Red Spruce, Yellow Birch, Balsam Fir, Red Maple Beech Community		Sugar Maple, Beech Community		Sugar Maple, Beech, Yellow Birch Community	
TM var.	r	TM var.	r	TM var.	r
		June 17, 1984			
(n = 41)		(n = 32)			
#3/1	-.588***	2	-.640***		
#3	-.515**	2/1	-.622***		
3/2	-.505**	6/2	+.595**		
7/5	-.474	#3/1	-.588**		
#6/3	+.467	#3	-.581**		
7/4	-.434	#6/3	+.510		
(4-3)/(4+3)	+.407				
		September 21, 1984			
(n = 36)		(n = 32)		(n = 34)	
#7/5	-.527**	#7/5	-.510	2/1	+.446
		Merged June/September			
(n = 36)		(n = 27)			
June (4-3)/(4+3)	+.470	June 2	-.640**		
June 4/3	+.456	June 7/5	-.622**		
June 3/2	-.451	June 2/1	-.621**		
#June 3/1	-.427	June 7	-.587**		
		June 7/1	-.578		
		June 7/4	-.577		
		June /3	-.520		
		#June 3/1	-.504		
		June 7/2	-.490		

Note: Community types not tabulated did not produce significant correlations or had too small of a sample.

Table 9. Correlations between TM band values and plot forest productivity data for New York, June, September, and merged TM scenes. Correlations are based on stratification of plots by general aspect directions. Only correlations in which p<.01 are shown. If p<.001 then **, p<.0001 then ***. If variable is significant for more than one aspect then #.

Aspects E, SE, S		Aspects N, NE, NW		Aspects SW, W	
TM var.	r	TM var.	r	TM var.	r
		June 17, 1984			
(n = 44)		(n = 46)		(n = 65)	
(4-3)/(4+3)	+.407	7/4	-.463**	#2/1	-.536***
4/3	+.395	#7/5	-.441	#3/1	-.494***
4/2	+.389	5/4	-.428	#2	-.485***
(4-3)/(4+3)	+.385	#3/1	-.424	#3	-.452**
3/1	-.384	#2/1	-.388	6/2	+.400
		#2	-.377	6/3	+.385
		#3	-.374	7	-.362
				#7/5	-.358
				7/1	-.349
				7/6	-.348
		September 21, 1984			
				(n = 59)	
				3/2	+.532***
				3/1	+.358
		Merged June 17, 1984 and September 21, 1984			
		(n= 45)		(n = 57)	
		#June 7/4	-.518**	June 3/1	-.474**
		#June 7/5	-.486**	June 3	-.451**
		June 5/4	-.482**	#June 2/1	-.437**
		#June 2	-.417	#June 2	-.431**
		#June 2/1	-.411	June 3/September 3	-.425**
				June 7	-.410
				#June 7/5	-.407
				June 7/1	-.405
				September 3/2	+.405
				#June 7/4	-.383

Note: Correlations for aspects not tabulated were not statistically significant at the 0.01 level.

to which the spectral data are sensitive, (2) stratifying the data to achieve more homogeneity among the plots improved the correlations, and (3) larger sample numbers were needed to be able to make meaningful comparisons among some of the strata.

Table 10 shows the two best variables correlated with forest productivity for the three TM data sets when stratified by forest community type. The best overall correlation with forest productivity was TM Band 2 from the June data set for a sugar maple/beech community type (-0.64, p=<0.0001). A strong inverse correlation of productivity to TM Band 2 during the growing season is intuitively logical since higher amounts of chlorophyll in vegetation causes TM Band 2 values to decrease due to absorption (Badhwar et al., 1984). Healthier, more productive vegetation, therefore, would have lower TM Band 2 values. The sugar maple/beech community type was also one of the most homogeneous with few conifer mixtures. In June, the visible band data were more correlated to productivity, whereas in the September data, the infrared bands carried the highest correlations (Tables 8 and 10). Similar results were found in the Smoky Mountain data when comparing September to October data. For the higher latitude of New York, September would be analogous to October in the Smoky Mountains in terms of fall foliage, so the argument as to the importance of infrared bands at the margin of the growing season would be the same as discussed above in the Smoky Mountains section.

When stratifying by aspect, it can be seen that the visible band combinations generally correlate better to productivity on more illuminated slopes (E, SE, S, SW, and W), whereas nearand mid-IR bands are more important on the shadowed, northerly slopes (Table 9). It seems that when strata were based on aspect as opposed to vegetation types, the differences between TM dates and their corresponding leaf conditions were

Table 10. Best correlations of TM values to plot forest productivity data in New York, all data sets, when stratified by community types. Only correlations in which $p<.01$ are shown. If $p<.001$ then **, $p<.0001$ then ***.

Date	TM Variable	r	Community Type
June 1984	2	-.640***	sugar maple, beech (n = 32)
	2/1	-.622***	sugar maple, beech (n = 32)
Sept 1984	7/5	-.527**	red spruce, yellow birch, balsam fir, red maple, beech (n = 36)
	7/5	-.510	sugar maple, beech (n = 27)
Merged	June 2	-.640**	sugar maple, beech (n = 27)
	June 7/5	-.622**	sugar maple, beech (n = 27)

not as critical to correlations as were the degree of illumination. Northerly slopes, with less contamination from high variability of illumination, may better represent the interplay in productivity of vegetation density and moisture content to which the IR bands are sensitive. However, given that fewer variables correlated significantly or as strongly when stratified by aspect as did when stratified by community types, the community types appear to be more determinate of productivity in this region than aspect and elevation, which were greater importance in the Smoky Mountains. This could be due, in part, to the fact that moisture stress (a manifestation of heat) is not generally a limiting factor to productivity in New York but can be in the Smoky Mountains. In support of this fact, note that the thermal band played no role in highly significant variables in New York, even when stratified by aspect, whereas Band 6 was the major factor in the Smoky Mountain analysis.

d. Comparisons Among Sites

When comparing correlations among sites the following points become clear: (1) ratios of TM bands correlate better than single bands or vegetation indexes, (2) stratifying, when sample sizes are adequate, improves correlations by way of reducing spectral variance in the data from factors other than productivity, (3) the best correlations to productivity are TM variables in the visible bands in some cases and in the infrared bands in other cases, depending largely on forest phenology in the region and time of the TM data, (4) thermal information has an important relationship to productivity in regions where elevation and aspect dramatically effect forest communities, especially due to moisture stress, and (5) no single band, band ratio, or other band combination stood out across all sites in correlating to forest productivity because

of too many other factors at each location contributing to the overall variance. This points to the next logical step being multiple regression, where the interplay of more than one variable, including biogeographical data not pertaining to the TM values, can be considered.

2. Regression Modeling

a. Southern Illinois

Multiple regression techniques revealed a combination of independent variables related to MAI. All variables previously mentioned were regressed against MAI, with the proviso that multi-collinearity diagnostics were monitored to avoid violation of regression assumptions. The variables entering the best regression model, in order, were TM 7:4 ratio, soil woodland productivity index, and TM 2:1 ratio, according to the following equation:

$$MAI = 201.3984 - 313.2450(TM7/4) + 0.03949\ (\text{soil prod. index}) - 391.9469(TM\ 2/1) \quad (2)$$

Addition of other variables failed to contribute significantly to the model due to collinearity. Earlier studies have indicated that TM data provided the most information on an ecosystem when a mid-IR, near-IR, and visible band were considered in the analysis (Dottavio and Williams, 1982; Haas and Waltz, 1983; Badhwar _et al._, 1984; Spanner _et al._, 1984; Benson and DeGloria, 1985; Sheffield, 1985). Each of these spectral components are included in the best 3-variable model. Acknowledging the role of site characteristics in predicting productivity, the inclusion of soil productivity in the model is important and underscores the ability to include new independent information in models when biogeographical data

are used. The 3-variable model was highly significant ($p=<.002$, $n=32$), indicating a good approximation of where the line should be, but high amounts of scatter caused the adjusted r^2 to be low (0.39) and resulted in a fairly poor MAI predictability curve (Fig. 10).

Correlation and regression statistics were also performed with standing growing stock, i.e., volume, rather than MAI, as the independent variable. These relationships were weaker than those to MAI, suggesting that TM spectral data provide more information on productivity than biomass; this in agreement with the theoretical interpretation of the sensor by Tucker and Sellers (1986). However, the ability to analyze these in much detail is limited by the small sample size, and more elaborate discussion is saved for the other areas below.

b. *Great Smoky Mountains*

Because of a high degree of correlation among independent variables, collinearity was a major problem in developing multiple variable regression models. In fact, once models with collinearity problems had been discarded, there were no multiple variable models that were significantly better than the single variable models.

Highly significant relationships between TM variables and forest productivity were demonstrated; however, there was always a large amount of unexplained variability (Table 11). This is due, in part, to the extreme shade-sunlight variations resulting from the low morning sun angle and the mountainous terrain which caused the band values to be highly correlated with each other. Other unexplained variability may be due to (1) errors in the productivity measurements (only the volume growth of large trees in the stands were considered [Section III, B.3.b]), and (2) the multi-species nature of these forests.

Fig. 10. Regression of 3-variable model to mean annual increment (MAI) in Illinois.

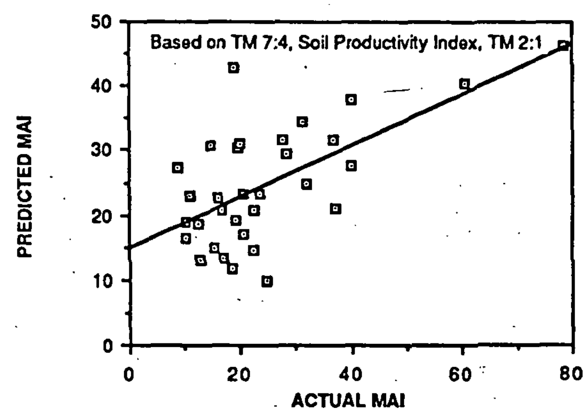

Fig. 11. Regression of TM6: TM1 to forest productivity in the Smokies. Confidence intervals for individual pixels and the landscape are portrayed.

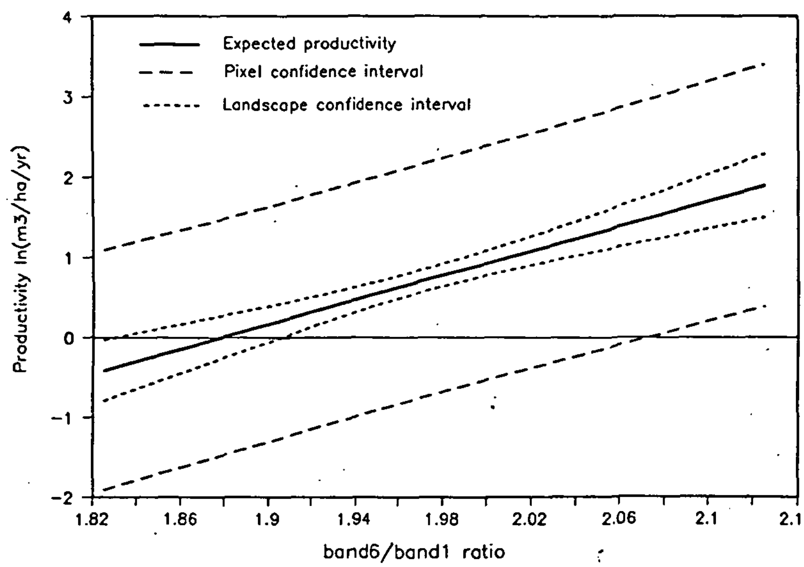

Fig. 12. Regression of 3-variable model to productivity in the Huntington Wildlife Forest, NY.

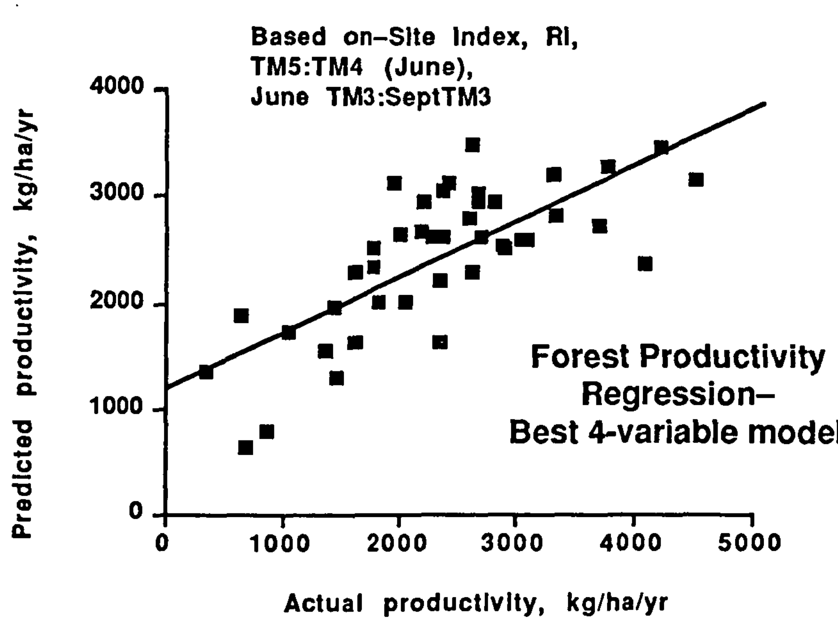

Table 11. The best models to predict forest productivity from TM data and biogeographical data (forest type, slope, elevation, aspect) using various combinations of techniques.

BEST MODELS BY METHODS

METHODS	VARIABLES IN MODEL	n	r2	P<
REG, STRAT, BG	band6/band1	111	.269	.0001
REG-PRINC, STRAT	PCA3	94	.145	.0002
REG-PRINC, STRAT, BG	Elevation	111	.191	.0001
REG, BG	band6/band1	128	.152	.0001
REG-PRINC	PCA3	105	.113	.0004
REG-PRINC, BG	Elevation	128	.136	.0001
CLASS, ANOVA	6 classes	111	.181	.0007
CLASS, ANOVA, BG	6 classes, elevation	111	.232	.0001
CLASS, ANOVA, STRAT	6 classes	97	.163	.0056
CLASS, ANOVA, STRAT, BG	6 classes, elevation	97	.247	.0002

TECHNIQUES

REG = Multiple regression modeling using TM band values, TM band ratios, and TM vegetation indices. NOTE - Although multiple variables were allowed to enter the models, in no instance did a multiple variable model prove better than a single variable model if collinearity among variables was controlled for.

STRAT = Allowing only hardwood and mixed pine-hardwood stands in the analysis.

ANOVA = Analysis of variance of class data generated by CLASS.

REG-PRINC = Principal Component analysis to generate principal component TM variables called PCA1- PCA7 followed by multiple regression using PCA1-7 values.

CLASS = Unsupervised classification (using all 7 bands) of TM scene to classify pixels.

BG = allowing a biogeographical variable to enter the regression model if it improved the model. (the variables listed were the best predictors)

The high significance ($p=<0.0001$) but high unexplained variance in forest productivity (low r^2) of these models means that the models can be used to accurately predict the median or average forest productivity of many pixels but cannot be used to project the productivity of any one pixel. Consequently the models are useful for evaluating the overall productivity of forest on the landscape but not the spatial pattern of that productivity. Statistically this is a consequence of the fact that the parameters of the model are well estimated (in part due to the many data observations, n>100), even though the individual error terms are large. For example, the model which best accounted for the observed variability in forest productivity in this rugged terrain was a single variable regression model developed from the September TM scene and hardwood and pine-hardwood stand productivity data:

$$\ln(\text{productivity}) = -14.4 + 6.65(\text{TM } 6/1), \qquad (3)$$

$$r^2 = .269, \; n=111, \; p=<0.0001$$

This model can be used to predict the median hardwood/mixed-hardwood forest productivity over large areas (>100 pixels) with a high degree of accuracy ($\pm$ ca. 10 percent) (see confidence intervals in Figure 11.), while its ability to predict the forest productivity of any one pixel is poor (see pixel confidence intervals in Figure 11). Thus, the model is very useful in predicting the overall productivity of the landscape but not in predicting the fine-scale spatial pattern of productivity.

The results of the work in the Smoky Mountains demonstrates two important points. First, in mountainous terrain the topographic position of a forest stand will strongly determine its productivity. Thus, TM variables which relate to topographic features will be useful in

predicting forest productivity. Consequently, combining a band that directly measures a variable associated with topography and a TM band which relates to the quality of the vegetation will explain the most variance in forest productivity over a mountainous landscape. Second, although TM data cannot capture the precise patterns of productivity in the landscape, they can be used to evaluate the overall productivity of the landscape with a reasonable degree of precision. Thus, TM data could be useful in tracking the temporal pattern of forest productivity on the landscape.

c. Huntington Wildlife Forest, New York

Multiple regression analysis yielded a best model with an adjusted r^2 of 0.42 ($p=<0.0001$, $n=45$), using TM5/4 from June, June TM3/September TM3, soil productivity/site index, and sun radiance index, for N, NE, and NW aspects (Fig. 12). Not only does this regression support the correlation findings about improved relationships from stratification, but it also presents an interesting comparison to the Illinois study site. The best regression models for the two study sites each include a mid-IR to near-IR ratio, visible bands in some form, and soil productivity/site index. In each case, the best models of fewer variables consisted only of TM variables, and the addition of site characteristics improved the models.

Table 12 relates the best regression models found for each TM data set, using all plots as well as stratifications by aspect and community types. In all cases, models were improved when the data were stratified, achieving more homogeneity among plots. As was true for the other study sites, considerable variance in productivity is unexplained by the models (low r^2), although they are highly significant ($p=<0.0001$).

Table 12. Best models to predict forest productivity from TM data and biogeographical data for New York using all plots and stratifications by aspect and community types.

TM Data	n	Adj. r^2	p<	Variables
June				
All plots	160	.19	.0001	3/1, 7/5
by aspect (N, NE, NW)	46	.27	.0001	5/4, site index, sun radiance index
by community type (mixed*)	41	.33	.0001	3/1, 7/5, site index
Sept				
All plots	141	.13	.0001	3/2, 7/4
by aspect (SW, W)	57	.38	.0001	2, 3, 7/5
by community type (mixed*)	33	.27	.0001	6/4, 7/5
Merged				
all plots	138	.25	.0001	June 1/Sept 1, June 7/4 June 3/Sept 3
by aspect (N, NE, NW)	44	.42	.0001	June 5/4, sun radiance index, site index, June 3/Sept 3
by community type (mixed*)	33	.32	.001	Sept 7/5, site index, June 3/Sept 3

*Mixed is the red spruce, yellow birch, balsum fir, red maple and beech community type.

For New York, biogeographical data were more important in explaining productivity than at the other study sites. A high degree of hardwood-conifer mix in the forest communities confounds the TM/productivity relationship because of the very different reflectance patterns of conifers and hardwoods. Non-spectral data, such as site index, provide important additional information in explaining variance in productivity at these sites. Additionally, the overall better performance of the multi-temporal data set, especially with temporal ratios of the same bands, indicates that seasonal changes in hardwoods, e.g., chlorophyll, have strong relationships to productivity, in contrast to the role heat and moisture extremes play in determining productivity in the Smoky Mountains.

Regression results, while improved with stratification, were overall not as good as was hoped for, considering that this site had the largest sample of plot data as well as multi-temporally combined TM data. Several factors probably contributed to the problems. First of all, one cannot be absolutely certain of a precise alignment of TM data and productivity plots to the coordinate system. Small inaccuracies in such a heterogenous landscape could skew the analyses. Secondly, the area is complex in terms of forest communities, most of which are mixtures in varying degrees of hardwoods and conifers, and mixed communities occur at all elevations, unlike in the Smoky Mountains. Thirdly, the phenology of the vegetation at the times of the TM data may not have been the best possible situation (too early in the growing season on June 14 and too late on September 21). Finally, the TM DN values and their ranges were smaller because of a high degree of water and boggy areas and they were, therefore, not as sensitive to the vegetation characteristics as for the other study areas.

d. Comparison Among Sites

In general, the regression models of all study areas were highly significant but left a great deal of variance in forest productivity unexplained. This is a similar finding with other studies of forest structure, biomass, or productivity. Because of extreme heterogeneity of forest stands at the 30 m x 30 m resolution and the many abiotic and biotic variables acting on an ecosystem, it is not reasonable to expect a high degree of predictability on small, site-specific areas (Franklin, 1986; Peterson et al., 1986). However, by changing the scale of reference to cover larger areas, or by pooling and/or stratifying data, predictability can be improved. For example, by stratifying observations according to species/basal area classes and replacing individual observations by class medians, Franklin (1986) found r^2 values increasing from 0.29 to 0.67 in regressing single-band data to conifer foliar biomass. Stratifying by community type and aspect in New York was also found to improve regression fits considerably over unstratified data while maintaining very high significance levels (Cook et al., 1987).

The results shown here are encouraging for the potential to use TM spectral data in combination with ancillary data to produce regional forest productivity estimates. By creating an image file with scaled TM 7/4, soil woodland productivity index, and TM 2/1 as the channels, the regression equation (2) was then applied to each pixel of northern Pope County, Illinois, to produce an output image of MAI estimates for the deciduous forests in the area. Classifying these further into seven productivity classes and smoothing with a 3 x 3 window filter reduced some of the inherent spatial variability and resulted in a map of estimated forest productivity (Fig. 13). The total production for this portion of Pope County (14,724 ha of deciduous forest) was estimated to be 20,949 cu

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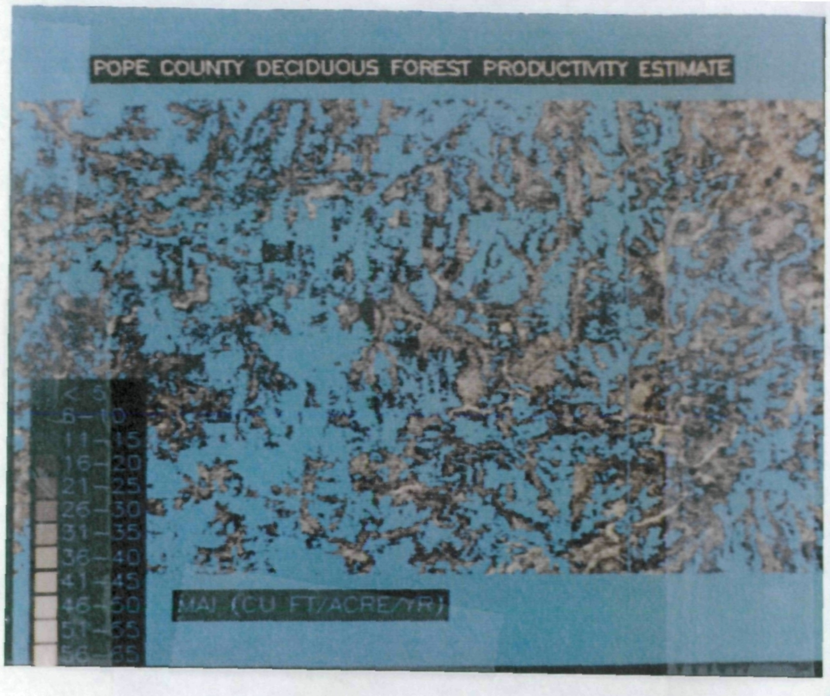

Fig. 13. Estimated productivity for deciduous forests in northern Pope County, Illinois; based on regression model presented in Fig. 10.

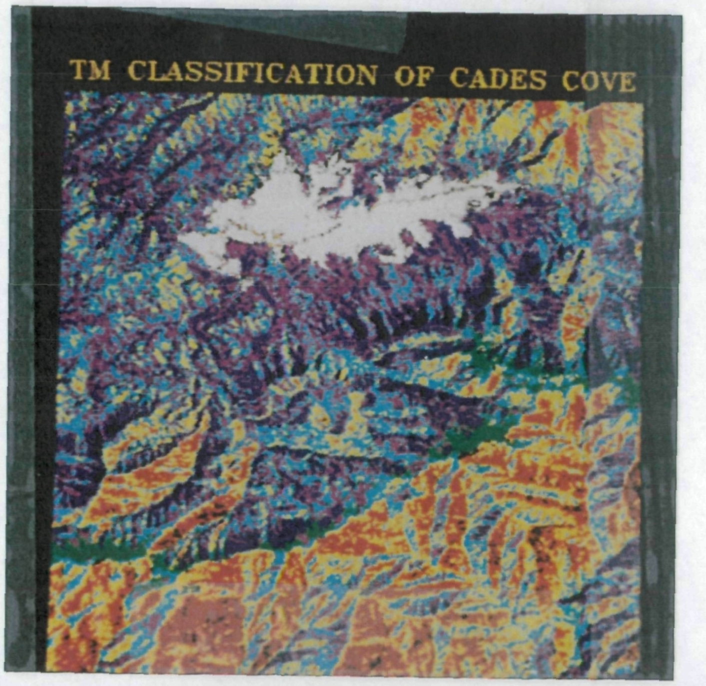

Fig. 14. Two-dimensional portrayal of productivity classes for Cades Cove Quadrangle in the Smokies. Blues and purples are most productive; yellow and greens, the least.

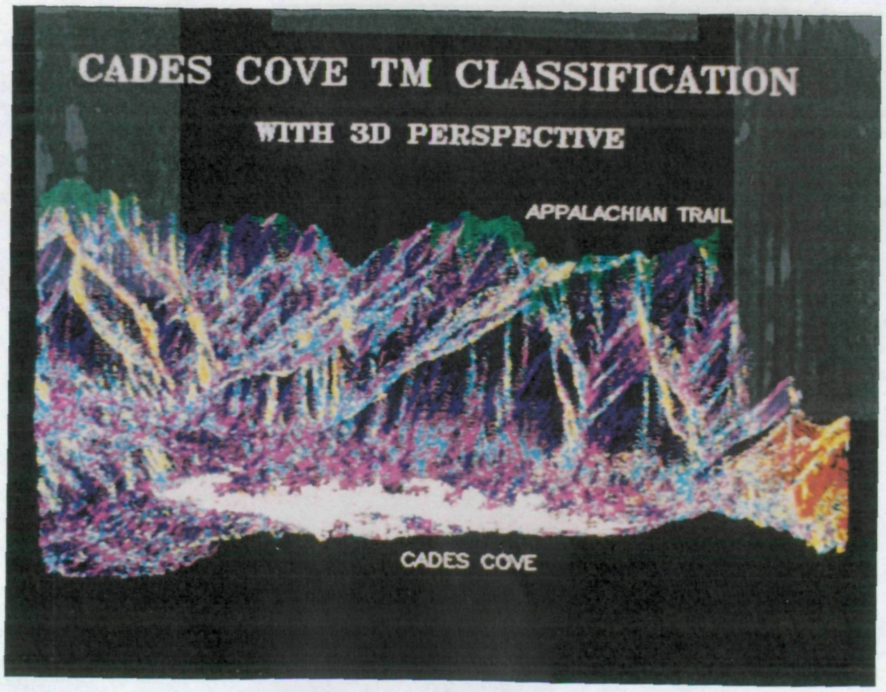

Fig. 15. Three-dimensional portrayal of productivity classes for Cades Cove Quadrangle as viewed from the NW; classes delineated as in Fig. 14.

m/yr. Assuming similar productivity across the entire county, which contains an estimated 44,720 ha of deciduous forest (Hahn, 1987), one can calculate a total county production estimate of 63,628 cu m/yr. The 1985 U.S. Forest Service estimate, using conventional ground-sampling methods, was 87,244 cu m/yr for the entire county. The U.S. Forest Service estimate at the county level was based on 49 forest plots, and could be expected to have a sampling error of about 20 percent (Hahn, 1987). This, along with the inevitable errors associated with the remotely-sensed estimate because of the incomplete sample (one-third of the county) and the low r^2 of the regression equation, can account for the differential of 25 percent between the two estimates. Clearly, additional efforts need to be conducted to test and validate the relationships, but these initial results reveal an encouraging potential to use this methodology for estimating forest productivity over relatively large areas. The relationship of these TM-productivity regression-model estimates to AVHRR spectral values, with ultimate extension to a multi-state region, was one attempt to validate the technique, and is discussed below.

3. Classification/ANOVA

a. Great Smoky Mountains

All three ANOVA techniques successfully used the TM and biogeographical data to explain a statistically significant proportion of the observed variance in productivity (Table 11). Using the biogeographical data either to stratify the observations or as a covariate in ANOVA improved our ability to use TM data to predict forest productivity (Table 11). The use of elevation as a covariate improved the model significance considerably. There were no significant TM class-elevation interaction effects. Plot aspect did not explain a

significant proportion of forest productivity. Of the biogeographical variables, only plot elevation varied significantly among the TM-classes. TM data were most useful in their raw state. Deriving the principal component values of the TM data prior to relating the spectral information to forest productivity was not beneficial in explaining forest productivity variance.

Using results from ANOVA to assign productivity values to the TM classes, a productivity map for Cades Cove quadrangle was produced in two (Fig. 14) and three (Fig. 15) dimensions. These figures show, in blues and purples, the highest productivity cove sites; the yellows and greens show the less productive higher elevation sites. The addition of the third dimension can be seen as a valuable visual aid in interpreting the results. The productivity map was also used for the AVHRR scale-up in the Smoky Mountain region.

B. TM/AVHRR Scale-Up

1. Percent Forest Estimation

a. Southern Illinois

Percent forest, as ascertained by TM classification, and certain AVHRR spectral characteristics were significantly correlated within the Jackson County, Illinois, calibration center. The NDVI calculated from AVHRR data was correlated to percent forest cover ($r=0.585$, $n=154$, $p=<0.0001$), as were individual AVHRR Bands 1 ($r=0.599$, $n=154$, $p=<0.0001$) and 2 ($r=0.334$, $n=154$, $p=<0.0001$). The best 2 band regression model, violating no assumptions related to multi-collinearity and having an adjusted r^2 of 0.407, used a combination of Bands 1 and 2 as shown in equation (1) of Table 13. This equation, when applied over the Illinois AVHRR study area for the pixels which had been classified as

Table 13. Regression equations relating TM and AVHRR spectral data.

	Region	Dependent Variable	Regression Equation	Adj R^2	P	N
1.	Illinois	Percent Forest	232.0 - 3.056 (AV1) + 0.615 (AV2)	.41	<.0001	154
2.	Illinois	Percent Forest	59.9 - 1.822 (AV1) + 0.443 (AV2) + 1.541 (AV4)	.49	<.0001	154
3.	Illinois	Productivity, Cu m/AV pixel	-378.6 + 1314.71 (AV2 - AV 1)/(AV2 + AV1)	.32	<.0001	154
4.	Smokies	Percent Forest	-221.8624 + 2.151398 (AV4) + 940.428929 (AV3/(AV4 * AV1)	.57	<.0001	99
5.	Smokies	Productivity Cu m/AV pixel	-253.643 + 49.93923(AV3/AV1)	.51	<.0001	99
6.	Smokies	Productivity ln Cu m/AV pixel	-32.62848 + 90.18815 (AV2 - AV1)/(AV2 + AV1) + 56.2267 (AV3/(AV2 * AV1))	.53	<.0001	99

having some forest, produced a mean of 31.0 percent forest, a standard error around the mean of 4.9, and with 95 percent confidence limits at the overall mean of 21.3 to 40.6 percent. The pixels classified as having some measurable forest in the region (63.31 percent of all pixels), in other words were, on average, 31 percent forested. Calculating through for non-forested pixels (row-crop agriculture, urban centers, water), the mean calculated AVHRR-estimated percent forest was 19.6 percent, with 95 percent confident limits of 13.5 to 25.7 percent. This compares to the USFS calculated mean for the area was 20.8 percent forest, well within the expected range.

When all four AVHRR bands were included in the model, the best model accounted for 48.5 percent of the variance and included Bands 1, 2, and 4, according to equation (2) of Table 13. Error estimates were not calculated for the 3-variable model.

Regression equation (1) of Table 13 was applied to each pixel in the 10-state AVHRR data set of June 4, 1987 (Fig. 5), and classified into seven classes to produce a map depicting percent forest class over the entire area (Fig. 16). The map shows vast regions of Illinois and Iowa with very low forest cover, with increased forest percentage in the Ozarks and Mark Twain Forest of Missouri, the Hoosier Forest of Indiana, some southwestern Michigan forests, much of Wisconsin, and the Shawnee National Forest of southern Illinois. To test the validity of this map, a comparison was made to U.S. Forest Service estimates of percent forest by county (Fig. 17). The two maps generally are in agreement, but visual comparisons are difficult because of the differing scales of resolution. By summing the AVHRR estimates by county, a new county-resolution estimate with AVHRR data is achieved (Fig. 18). The resulting map can then be overlayed with the U.S. Forest Service data to produce a difference map (Fig. 19).

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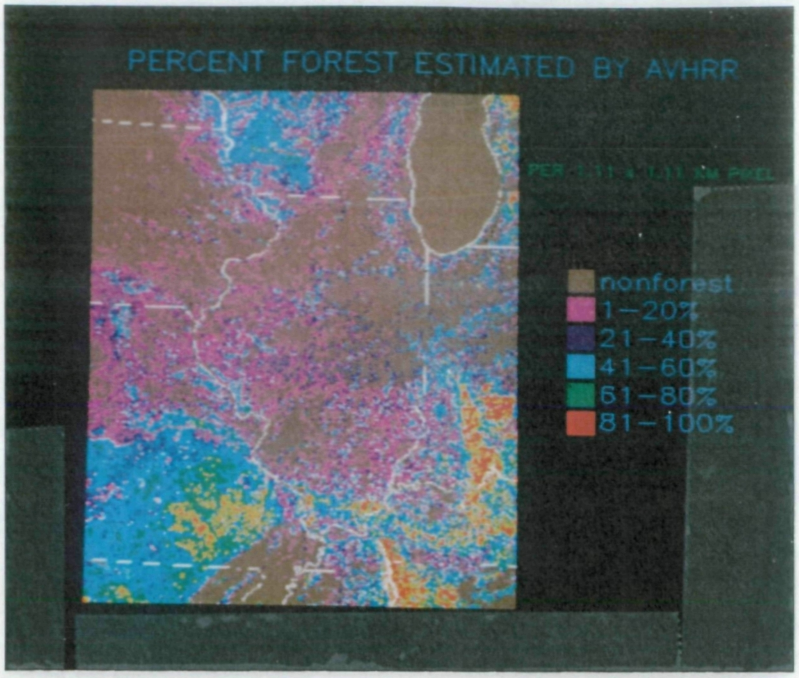

Fig. 16. Percent forest estimates by AVHRR pixels for Illinois region.

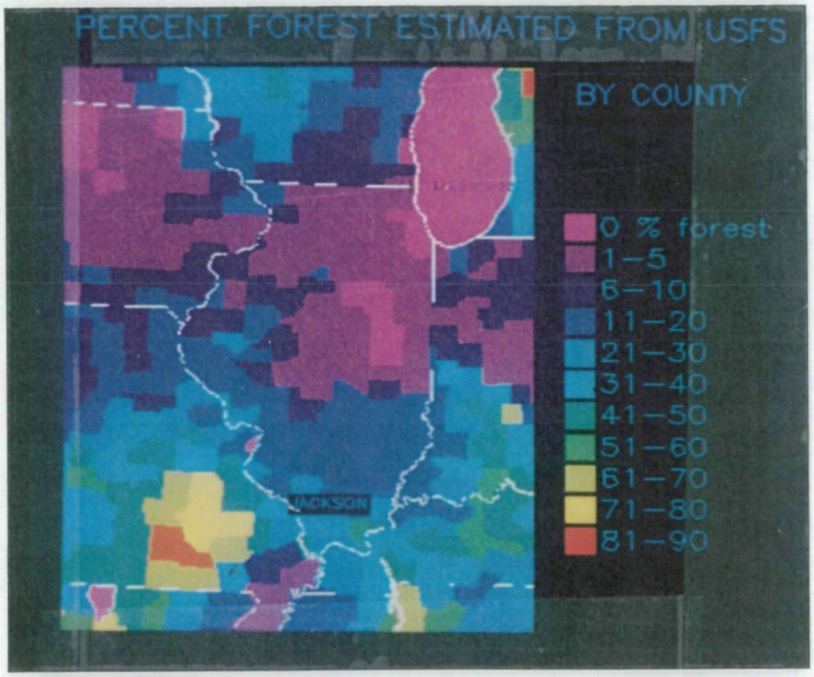

Fig. 17. County forest percentages as estimated by the USFS for the Illinois region.

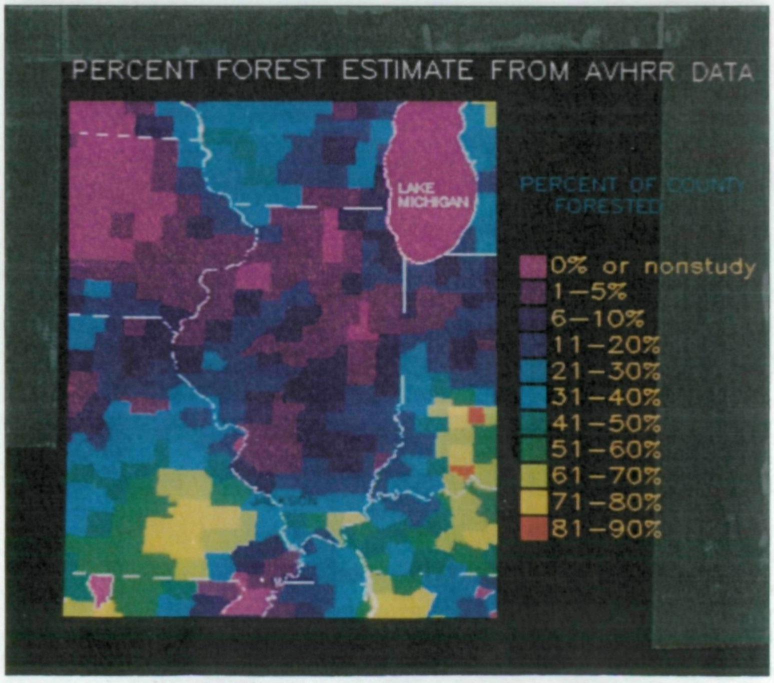

Fig. 18. County forest percentages as ascertained by aggregation of AVHRR pixels in Fig. 16.

Analysis of this map allows visual assessment of where AVHRR estimates differ most from the U.S. Forest Service estimates. For example, several western Indiana counties show AVHRR estimates more than 15 percent in excess of Geoecology estimates. This may be partially explained by the aged (1969 published date) U.S. Forest Service data from Indiana, and that there has been a trend toward increasing forest cover since that time in neighboring Illinois counties. The underestimation by AVHRR in the extreme southeast corner of the scene and along the eastern edge of Lake Michigan is the result of some cloud cover masking the AVHRR data in those areas. Correlation analysis revealed a very high relationship between the two estimates, with r=0.72 overall (Table 14, Fig. 20). When the difference map is compared to the buffer map depicting proximity to the calibration center in Jackson County (Fig. 2), one can see how the relationship holds up as one goes away from the center. When evaluated by buffer distance, the highest r values occurred within the 0 to 200 km radius (r=0.94), with the relationship slipping only slightly beyond 200 km (Table 14). Analysis of states with adequate samples showed highly significant correlation coefficients ranging from 0.72 in 36 Wisconsin counties to 0.96 in 77 Missouri counties.

Comparisons between means using pair-wise t-tests revealed a 2.7 percent higher estimate for the AVHRR data compared to the U.S. Forest Service data over all counties (overall estimate of 24.2 percent forest with AVHRR estimate and 21.5 percent with U.S. Forest Service estimate), which had a highly significant t value (Table 14). However, six of the ten states, accounting for over 70 percent of the total counties evaluated, did not have significant differences between AVHRR and U.S. Forest Service estimates. Counties within the 100 km buffer zone matched almost precisely (Table 14). Some of the differences between estimates can be accounted for

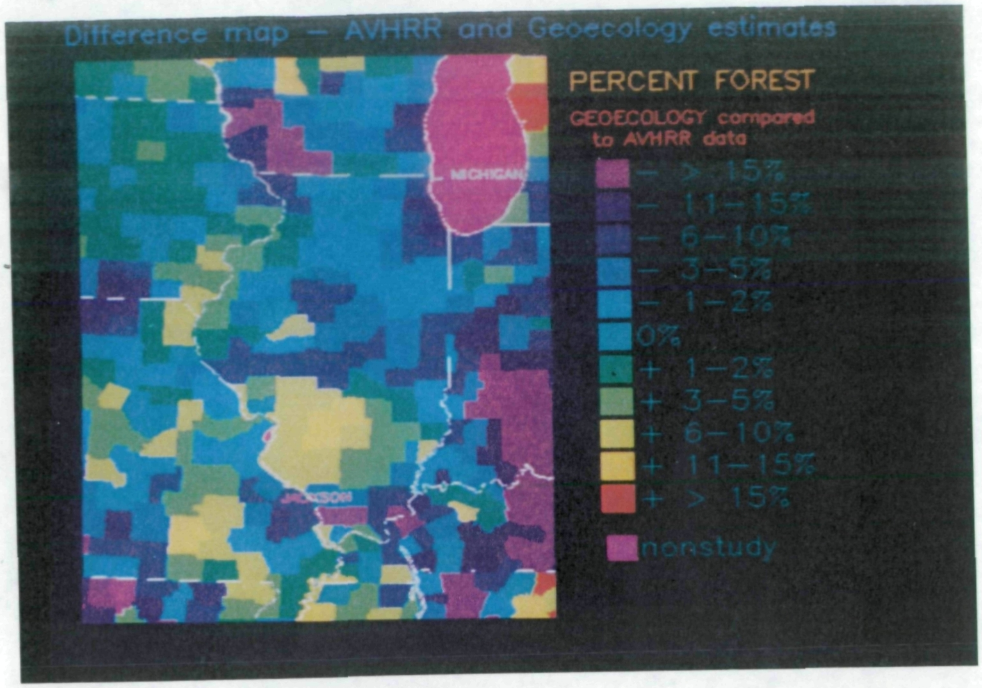

Fig. 19. Difference map depicting amount of discrepancy between USFS and AVHRR estimates of Illinois percent forest.

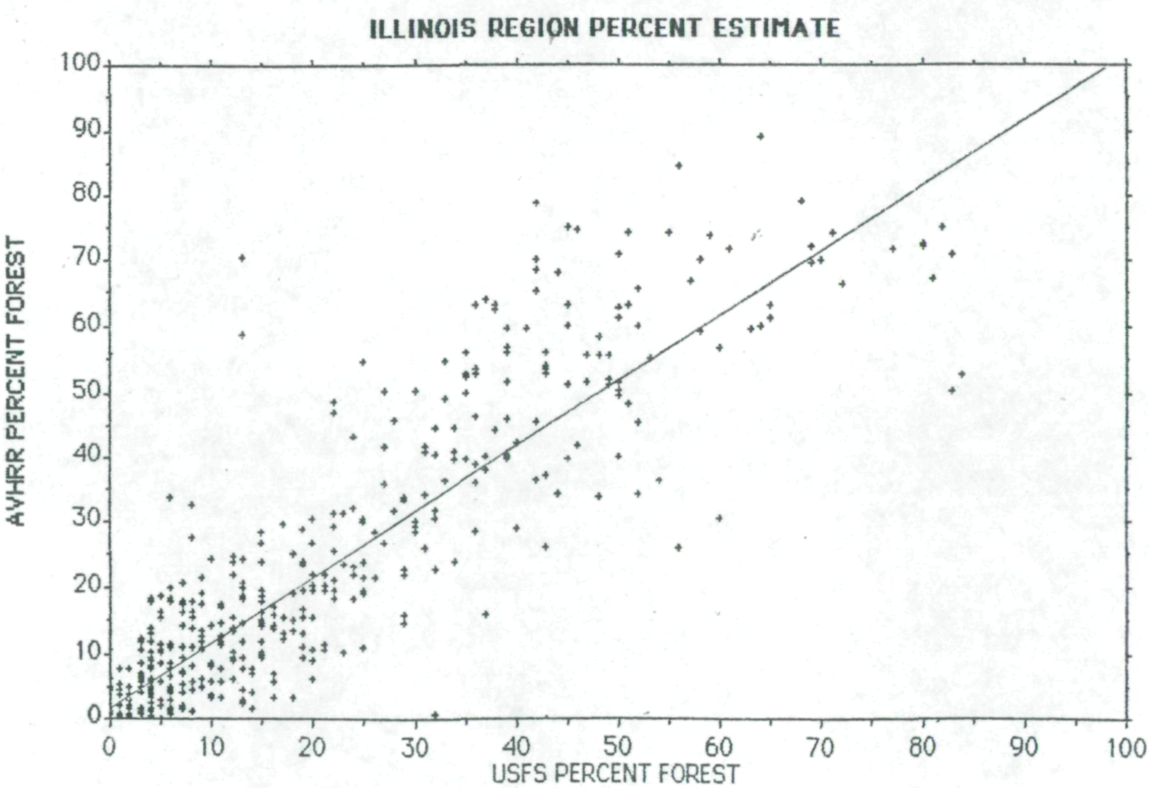

Fig. 20. Correlation between USFS and AVHRR estimates of percent forest over 432 counties in the Illinois region.

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Table 14. Percent forest estimates by AVHRR bands 1 and 2 and the US Forest Service. Data include T value and probability of means differing from each other, correlation coefficient between county estimates and its probability level, number of observations, and date the U.S. Forest Service data were published.

	Date	AVHRR (ave. percent forest)	USFS (ave. percent forest)	t	p	r	p	n
All by State	1965-1980	24.2	21.6	5.1	.0001	.87	.0001	432
Arkansas	(1980)	39.7	34.1	2.5	.0281	.93	.0001	15
Illinois	(1965)	12.7	12.0	1.0	.3429	.85	.0001	101
	(1985)		13.7	-1.9	.0590	.90	.0001	101
Indiana	(1969)	30.3	19.1	8.3	.0001	.91	.0001	62
Iowa	(1974)	4.5	4.9	-0.8	.4075	.80	.0001	55
Kentucky	(1978)	42.1	33.4	4.0	.0003	.72	.0001	39
Michigan	(1966)	35.6	41.8	-1.6	.1386	.78	.0048	11
Missouri	(1977)	32.8	32.6	0.3	.7469	.96	.0001	77
	(1972)		36.0	-4.7	.0001	.97	.0001	77
Tennessee	(1970)	34.1	36.6	-0.7	.4668	.80	.0001	24
Wisconsin	(1968)	24.6	22.8	0.8	.4583	.72	.0001	36
by Buffer								
0-100 km		28.5	28.4	0.1	.9450	.94	.0001	27
100-200		27.4	29.3	-2.1	.0355	.94	.0001	70
200-300		36.6	30.4	5.7	.0001	.88	.001	98
300-400		27.7	21.8	3.5	.0008	.70	.0001	83
> 400		12.1	10.9	1.9	.0550	.84	.0001	154

by real changes in percent forest in the time intervals involved. For example, a recent U.S. Forest Survey in Illinois indicated a 10 percent increase in forest acreage since the 1965 survey (Iverson et al., 1986); this could account for the higher value estimated by AVHRR. To test this hypothesis, two states (Illinois and Missouri) which had recent surveys were evaluated in the same manner. It was found that, for both states, the 1985 percent forest estimates were higher than the earlier U.S. Forest Service data, and that the correlation to AVHRR estimates was even higher. For Illinois, the new estimate was 13.7 percent forest with a correlation coefficient of 0.898, compared to 12 percent forest and 0.850 (Table 14). For Missouri, the new estimate was 36 percent forest with a correlation of 0.966, compared with 32.8 percent and 0.963.

Another difference between estimates is the definition of forestland. With AVHRR estimates, any group of trees regardless of where they are or how sparse they are, will reflect to the sensor. With U.S. Forest Service estimates, there are several categories called "non-forestland with trees" which do not enter into the final forest acreage estimates. Examples of this type include cropland with trees, wooded strips, urban forest, windbreaks, and wooded pasture. In Illinois, these categories accounted for 364,000 ha statewide, or 2.5 percent of the state (Iverson et al., 1986). For biospheric studies, large areas that are even more arid than Illinois are likely to show wider discrepancies of this same kind.

b. Great Smoky Mountains

For the Smoky Mountain region, there was again a highly significant relationship between TM-ascertained percentage of an AVHRR pixel forested and the spectral characteristics in the AVHRR data.

Equation (4) in Table 13 shows the best regression equation, with an adjusted r^2 of 0.57, using AVHRR Band 4 and a combination of Bands 3, 4, and 1.

As before, this equation was applied to all pixels in the region from the September 28, 1985, AVHRR data (Fig. 7); the result shows, as one might expect, the most dense cover in the Smoky Mountain National Park, with fairly high cover throughout except in the agricultural zones of central and western Tennessee (Fig. 21). Summation and averaging of percent cover for all pixels within a county allowed calculation of the estimated county coverage, which could, in turn, be compared to forest data acquired from the TVA (Table 15). Both the AVHRR (Fig. 22) and the TVA (Fig. 23) county estimates were mapped, as well as a difference map depicting county agreement (and disagreement) between the estimates (Fig. 24). The southeast corner of the scene was not represented due to the unavailability of TVA data for those Georgia and South Carolina counties.

Over all data points, the relationship between AVHRR and TVA estimates of county forest cover, were not that good. The correlation was a low, but highly significant, 0.47 (Table 16). Comparison of means by state show >20 percent underestimate by AVHRR in Georgia and South Carolina, and a 23 percent overestimate in 13 counties of Virginia (Table 15, Fig. 24). The influence of high amounts of conifer forests in Georgia and South Carolina (26 and 35 percent of the county forests, respectively) (Table 15) undoubtedly contribute to an underestimation of percent forest by AVHRR, since the pines are darker and cooler than the deciduous-dominated forests, such as the Cades Cove quadrangle where the calibration was done. This is borne out by the prevalence of underestimated counties in the Piedmont zones of Georgia and South Carolina (Fig. 24), and the fact that hardwood percent forest correlates

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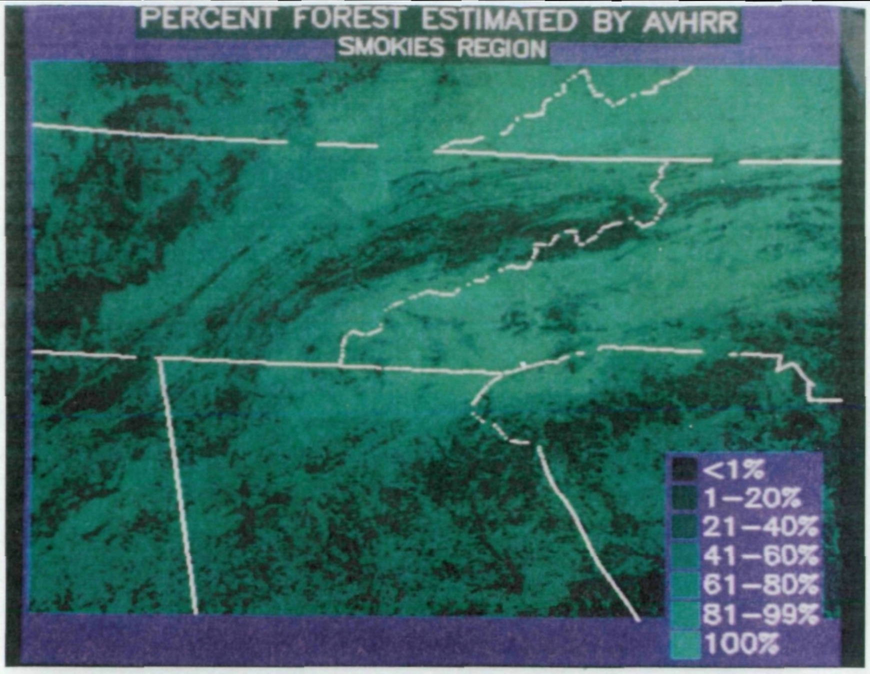

Fig. 21. Percent forest estimates by AVHRR pixels for Smokies region.

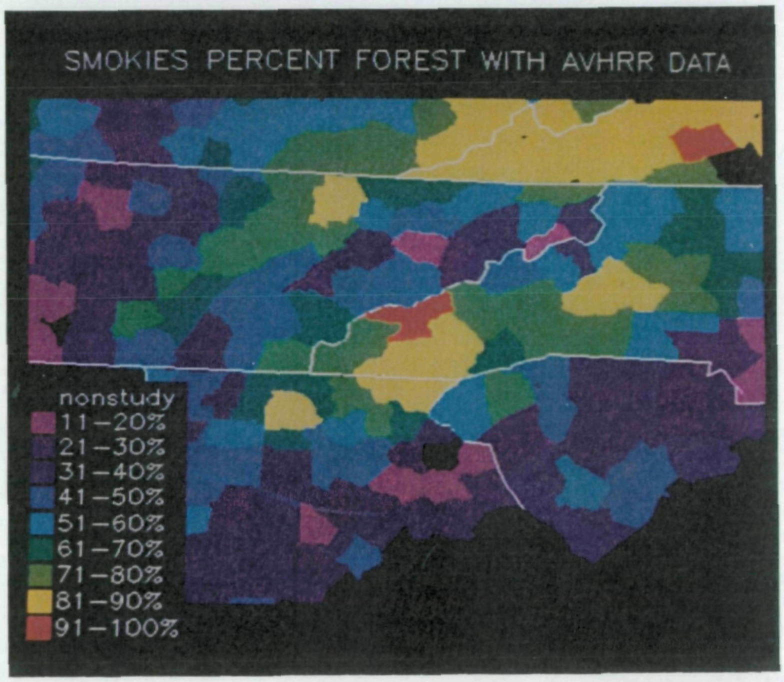

Fig. 22. County forest percentages as ascertained by aggregation of AVHRR pixels in Fig. 22.

Fig. 23. County forest percentages as estimated by TVA for the Smokies region.

Table 15. Percent forest estimates of the Smokies region from AVHRR and TVA data.

a. Over all counties with >75% of county in AVHRR scene

Category	AVHRR, %	TVA, %	Difference, %	Hardwood, %	Softwood, %	Mixed, %	N
All	52.2	62.6	-10.5	38.0	14.9	9.7	190
By Buffer							
0-100 km	62.3	69.4	- 7.1	41.3	11.9	16.2	28
100-200	53.8	66.2	-12.4	42.3	14.1	9.8	92
200-300	44.2	55.0	-10.7	30.3	17.8	6.9	67
By State							
GA	42.9	66.7	-23.8	29.5	26.1	11.1	50
KY	57.9	60.8	- 3.0	50.0	5.0	5.8	20
NC	66.7	67.9	- 1.1	44.7	11.7	11.5	32
SC	38.8	69.2	-30.4	24.0	34.5	10.7	18
TN	46.8	54.9	- 8.0	38.6	6.7	9.6	57
VA	84.9	62.0	23.0	52.5	4.2	5.3	13

b. Hardwood >40% of forest

Category	AVHRR, %	TVA, %	Difference, %	Hardwood, %	Softwood, %	Mixed, %	N
All	65.0	72.8	- 7.8	55.8	7.7	9.3	78
By Buffer							
0-100 km	72.9	81.1	- 8.3	55.4	12.5	13.2	16
100-200	63.6	74.4	-10.8	57.9	7.3	9.2	45
200-300	58.0	59.8	- 1.8	49.8	4.4	5.6	15
By State							
GA	66.6	85.6	-19.0	49.1	21.9	14.6	10
KY	65.9	75.6	- 9.7	63.2	5.6	6.8	12
NC	69.0	77.3	- 8.3	59.0	7.8	10.5	17
TN	54.6	67.4	-12.8	52.5	5.5	9.4	29
VA	85.9	64.7	+21.2	58.0	2.2	4.5	10

c. Mountains occupying >50% of county

Category	AVHRR, %	TVA, %	Difference, %	Hardwood, %	Softwood, %	Mixed, %	N
All	63.0	68.5	- 5.5	45.7	11.7	11.1	116
By Buffer							
0-100 km	62.3	69.4	- 7.1	41.3	11.9	16.2	28
100-200	61.4	69.8	- 8.4	48.0	11.8	10.0	67
200-300	66.3	63.4	2.9	44.0	12.4	7.0	18
By State							
GA	57.1	75.7	-18.6	37.4	25.3	13.0	23
KY	70.0	76.6	- 6.6	62.0	7.0	7.6	11
NC	71.2	75.7	- 4.4	51.3	10.8	13.6	24
TN	53.0	60.6	- 7.6	41.5	8.0	11.1	43
VA	84.9	62.0	23.0	52.5	4.2	5.3	13

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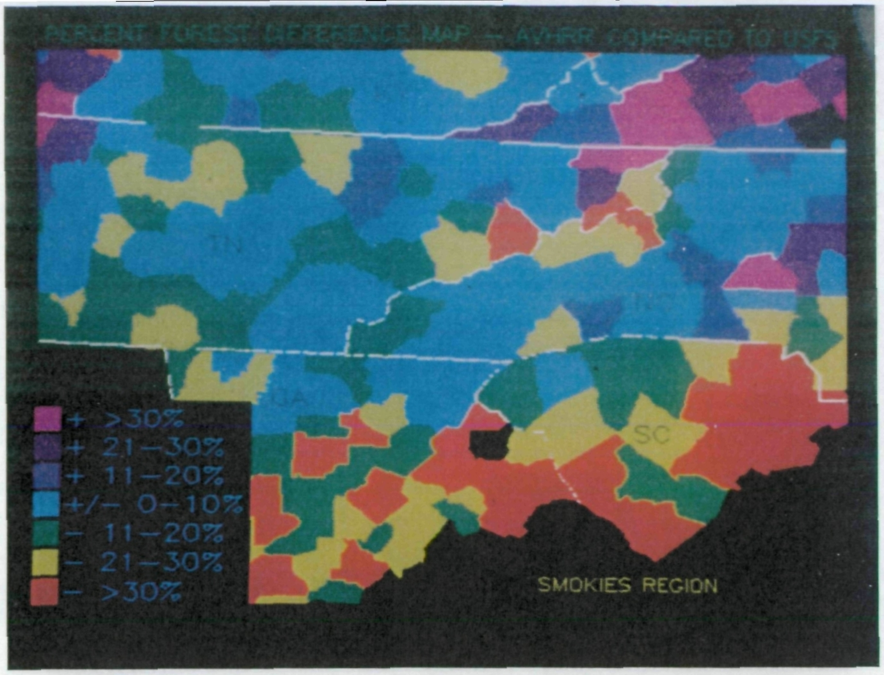

Fig. 24. Difference map depicting amount of discrepancy between USFS and AVHRR estimates of Smokies percent forest.

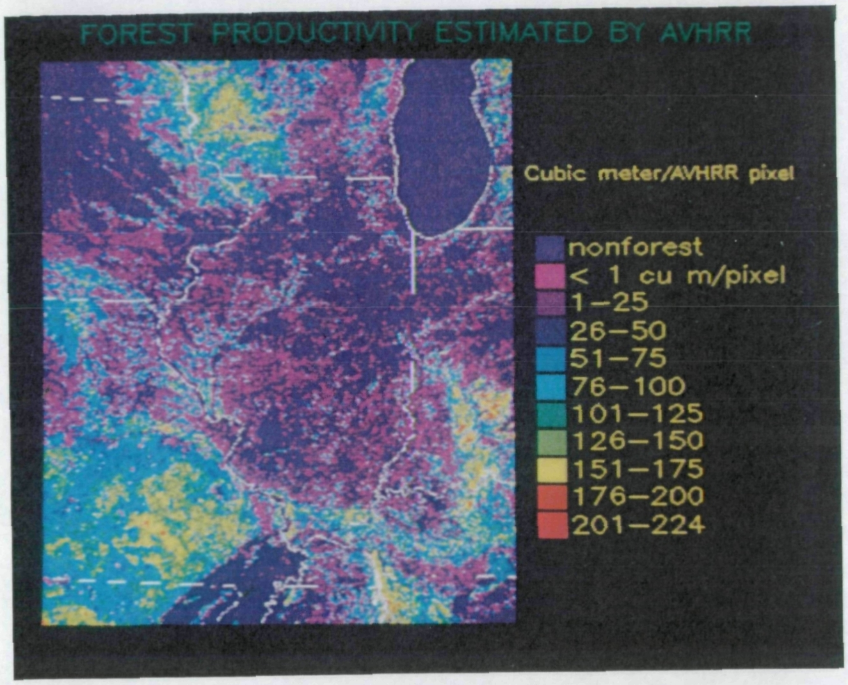

Fig. 25. Productivity estimates by AVHRR pixel for Illinois region.

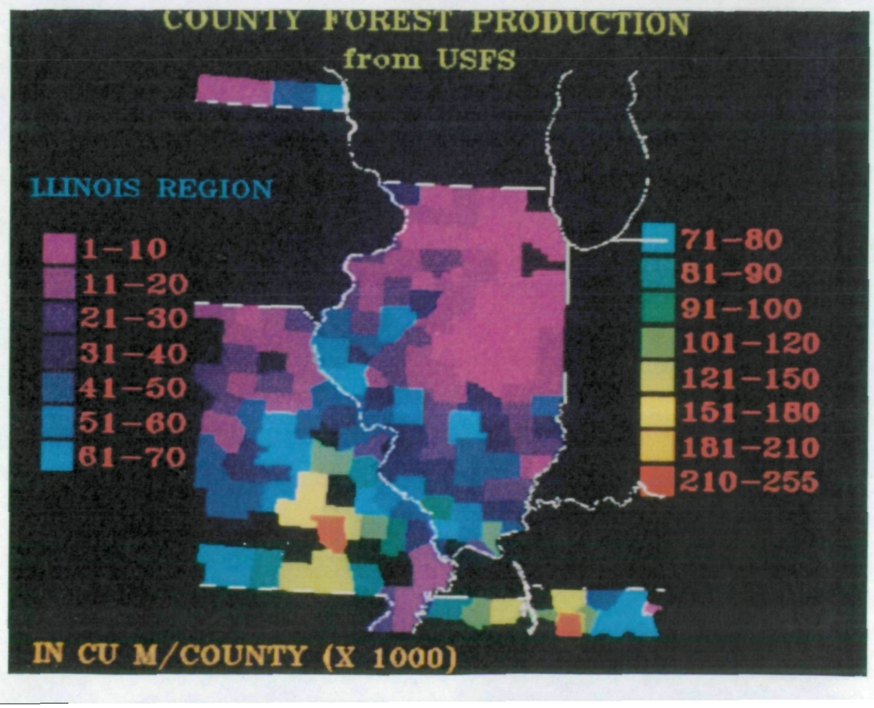

Fig. 26. County productivity as estimated by the USFS for the Illinois region.

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Table 16. Correlations of percent forest estimates from AVHRR to TVA data for Smokies region.

a. Over all counties with >75% of county in AVHRR scene

	Correlation of AVHRR estimated percent forest to TVA estimate of: Total Forest %		Hardwood Forest %		Softwood Forest %		
Category	r	P	r	P	r	P	N
All	.47	.0001	.58	.0001	-.26	.0003	190
By Buffer							
0-100 km	.84	.0001	.66	.0001	.17	.3981	28
100-200	.48	.0001	.56	.0001	-.31	.0023	92
200-300	.17	.1616	.50	.0001	-.21	.0845	67
By State							
GA	.68	.0001	.70	.0001	-.15	.3071	50
KY	.81	.0001	.76	.0001	.32	.1647	20
NC	.54	.0014	.21	.2532	.05	.7802	32
SC	.08	.7606	.23	.3486	-.14	.5812	18
TN	.62	.0001	.46	.0004	.24	.0682	57
VA	.00	.9975	.23	.4462	-.60	.0303	13

b. Hardwood >40% of forest

Category	r	P	r	P	r	P	N
All	.41	.0002	.34	.0025	.12	.3093	78
By Buffer							
0-100 km	.52	.0396	.41	.1190	.06	.8353	16
100-200	.31	.0416	.25	.0989	.08	.6219	45
200-300	.46	.0837	.53	.0404	.03	.9055	15
By State							
GA	.78	.0079	.46	.1821	.08	.8158	10
KY	.85	.0005	.69	.0132	.22	.4890	12
NC	.43	.0823	.08	.7714	.32	.2099	17
TN	.48	.0091	.29	.1248	.31	.0992	29
VA	-.15	.6718	-.22	.5611	.15	.6883	10

c. At least 50% of county mountains

Category	r	P	r	P	r	P	N
All	.43	.0001	.43	.0001	-.13	.1738	116
By Buffer							
0-100 km	.84	.0001	.66	.0001	.17	.3981	28
100-200	.35	.0036	.33	.0071	-.08	.5401	67
200-300	-.20	.4328	.42	.0804	-.54	.0203	18
By State							
GA	.59	.0033	.59	.0032	-.19	.3945	23
KY	.80	.0029	.77	.0057	-.50	.1192	11
NC	.42	.0397	-.20	.3477	.31	.1466	24
TN	.48	.0010	.38	.0121	.09	.5641	43
VA	.00	.9975	.23	.4462	-.60	.0303	13

much better to AVHRR estimates than softwood (Table 16). The Virginia overestimate is harder to explain. The vegetation of that portion of Virginia should be fairly similar to that in the Smoky Mountains, except that the spruce-fir zones were less than in Virginia. Consequently, higher DN's and higher predicted forest cover in the Virginia counties is the result (Fig. 23 and 24).

Correlation and mean comparison show a much better fit of the relationship for the other states (Kentucky, North Carolina, Tennessee). AVHRR-estimated means were 1 to 8 percent underestimated. Again, this slight underestimation is probably because of greater conifer forests overall than in the calibration zone, with correlations ranging from 0.54 to 0.81 (Tables 15 and 16).

Assessment of the relationship between the two estimates according to distance from the calibration center revealed a rapid decline in correlations. Within 100 km of Cades Cove the correlation was 0.84, but it dropped to 0.17 at the 200 to 300 km distance (Table 16). This indicates a greater specificity of the model to the calibration center in this highly heterogenous region.

Since the Cades Cove calibration center was located in hardwood-dominated, mountainous terrain, subsets of counties (hardwoods occupying over 40 percent of the county, and mountains occupying >50 percent of the county) are addressed in Tables 15 and 16. The trends are generally the same, however, for these subsets of data relative to the overall data set.

c. Comparison Among Sites

A much better agreement was found between USFS and AVHRR estimates of percent forest cover in the Illinois region relative to

the Smoky Mountain region. This can be attributed to the relative uniformity of landscapes and forest types and, therefore, similarity to the calibration center in the Illinois region; this was not the case in the Smoky Mountain region. Extreme variations in terrain and hardwood/softwood/mixed components for the Smoky Mountains undoubtedly contributed to the poorer relationship. However, with proper use of stratifications, multiple calibration centers, and multiple AVHRR data to differentiate hardwood/conifer zones, it is believed that this technique can be utilized with good results over any part of the globe. This is borne out by the good fit found within 100 km of the calibration center, and for some states having similar forest types and topography.

For relatively homogeneous and even sparsely-forested zones like Illinois, this technique provides rapid, inexpensive, and fairly precise estimates of percent forest over vast areas.

2. Productivity Estimation

a. Southern Illinois

As with percent cover, there was a high correlation between AVHRR-predicted county annual forest growth and the USFS estimated growth (r=0.72) (Table 17). This result was developed from the productivity model at the TM scale for northern Pope County, Illinois (Fig. 13), being related to spectral data in the raw AVHRR scene (Fig. 6). The resulting equation (3) of Table 13 predicts annual forest growth from NDVI within an AVHRR pixel, and when extended over a 10-state region, yields a map of productivity by pixel (Fig. 25).

For verification. USFS growth data were available for only four states: Illinois (1962 and 1985 data), Missouri (1972), Minnesota (1977), and Tennessee (1970); the county data are presented in Figure 26. The

Table 17. Illinois productivity by county as estimated by AVHRR and USFS. Data include means for AVHRR and USFS estimates, difference t values and probability of differing from each other, correlation coefficients between estimates, correlation probability levels, and number of observations.

	AVHRR (cubic meter growing stock/county)	USFS	Difference	t	p	r	p	n
All	39,300	43,000	- 3600	- 1.3	0.18	.72	.0001	176
by State								
Illinois (1962)	13,200	23,900	- 10,700	- 6.2	.0001	.57	.0001	99
Illinois (1985)	13,200	27,000	- 13,800	- 9.3	.0001	.71	.0001	100
Minnesota	44,300	34,000	10,300	1.3	.195	.99	.0002	4
Missouri	83,200	56,000	27,200	6.0	.0001	.83	.0001	58
Tennessee	43,000	105,600	- 62,600	- 5.5	.0001	.93	.0001	14
by Buffer								
0-100 km	37,300	51,100	- 13,700	- 3.09	.005	.86	.0001	26
100-200	46,900	63,600	- 16,700	- 3.70	.0007	.91	.0001	40
200-300	55,600	49,800	5900	0.80	.43	.56	.0001	51
300-400	21,000	22,600	- 1600	- 0.40	.69	.40	.0217	32
> 400	20,900	15,900	5100	1.18	.250	.79	.0001	27

AVHRR estimates were aggregated by pixel to yield a county map (Fig. 27) which, when overlayed with the USFS estimates map, produces a difference map (Fig. 28). One can see in this map, and in Table 17, an underrepresentation of forest productivity in Illinois and Tennessee, and an overrepresentation in Missouri, such that the overall means between the two are not significantly different. The reasons for the discrepancies are not clear; more work needs to be done along these lines. One possibility may be the geographic variation of the agricultural component in the landscape, and the large impact it has on the NDVI of an AVHRR pixel. The Pope County, Illinois, calibration center contains a smaller fraction of row-crop agriculture (barren at the May-June overflight dates) than nearly any other Illinois county, and a greater amount than most Missouri counties. Consequently, the NDVI and resulting production prediction may be lower in row-crop-dominated counties and higher in forest-dominated counties than we would expect from the calibration center.

The individual state estimates, though not in agreement with USFS production estimates, show highly significant correlations ranging from 0.71 to 0.93. This seems to indicate the potential for fine-tuning of the models and the addition of multiple calibration locations which would increase the precision of the models over large regions. Error in the USFS estimates also must be taken into consideration.

Correlations by buffer distance (compare Figures 2 and 28) revealed a very high relationship (r=>0.85) between estimates within a 200 km radius (Table 17). Beyond 200 km, the correlation values dropped off but continued to show a significant relationship. The mean values predicted by AVHRR were very close, however, to those estimated by the USFS, and were not significantly different in distance beyond 200 km (Table 17).

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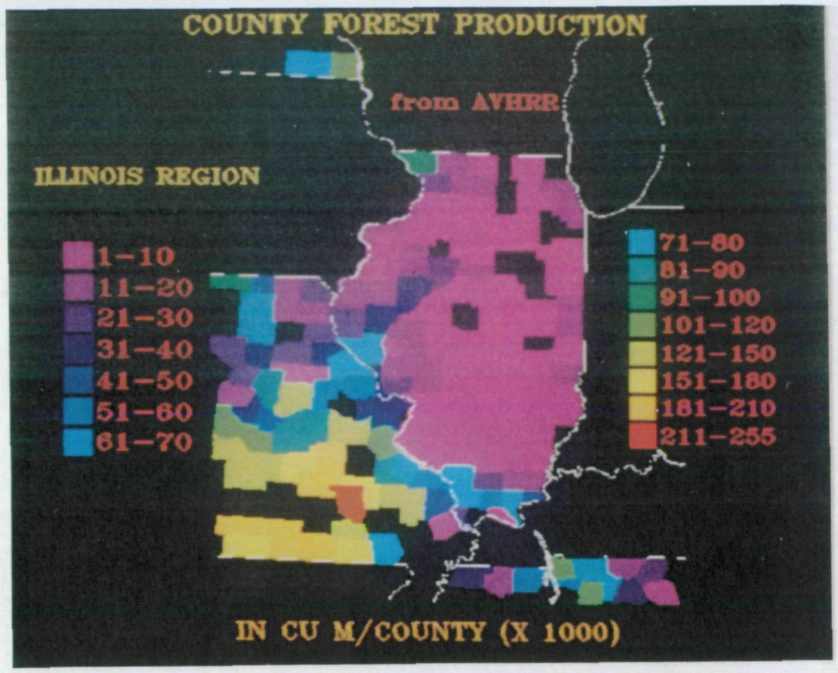

Fig. 27. County productivity for the Illinois region ascertained by aggregation of AVHRR pixels in Fig. 25.

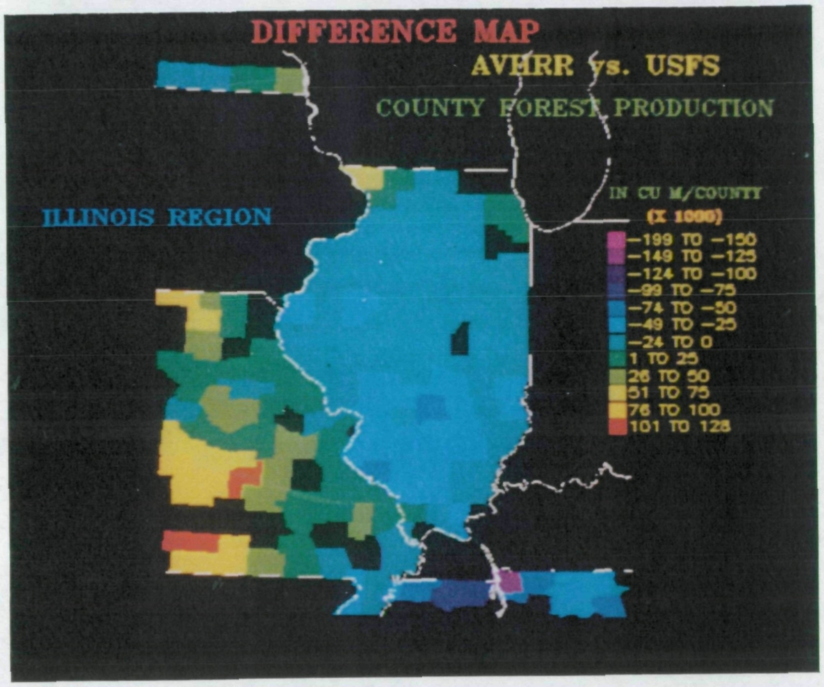

Fig. 28. Difference map depicting amount of discrepancy between USFS and AVHRR estimates of county productivity in the Illinois region.

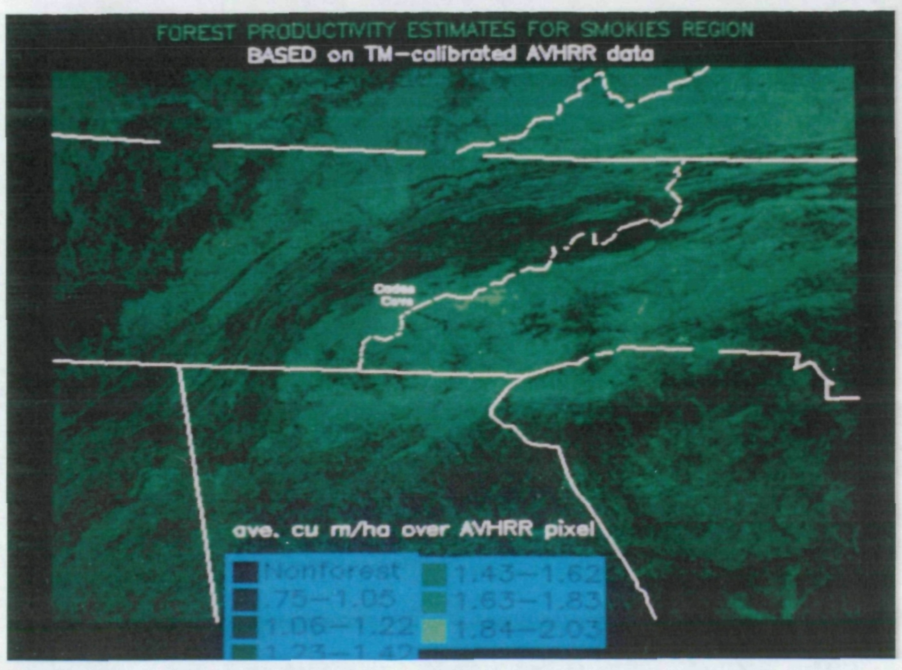

Fig. 29. Productivity estimates by AVHRR pixel for Smokies region.

b. Great Smoky Mountains

Calculations of regression relationships were performed with productivity estimates and a natural log transformation of productivity estimates (Callaway, 1983). These results are presented in equations (5) and (6) of Table 13; a little over one-half of the variance in productivity is accounted for by combinations of AVHRR spectral information. These regression equations were developed from classification predictions of Cades Cove productivity (Section III.C.3.a, Figs. 14 and 15).

Equation (5) of Table 13 was then applied to each AVHRR pixel in the region and grouped into seven productivity classes to yield a map of forest productivity (Fig. 29). As before, this map was aggregated by county to produce a map depicting county annual growth estimates in cubic meters per county (Fig. 30). This was compared to the TVA estimates for county annual growth (Fig. 31). AVHRR estimate was much below that of the TVA estimate.

The measures of productivity between USFS (TVA) and Callaway (1983) are not directly comparable as the methodologies were greatly different. Nonetheless, these two different measures of productivity can be compared in a correlative sense, as shown in Table 18. Analyzing the data in this way, the results are encouraging (Table 18). All correlations between estimates were significant, with most at the 0.0001 level. Total growth correlated with AVHRR estimates over 168 counties ($r=0.52$). Interestingly, softwood growth was correlated at $r=0.87$ for the same area (Table 18).

Evaluations by state indicate that with the exception of softwood production in South Carolina and Virginia, significant correlations exist

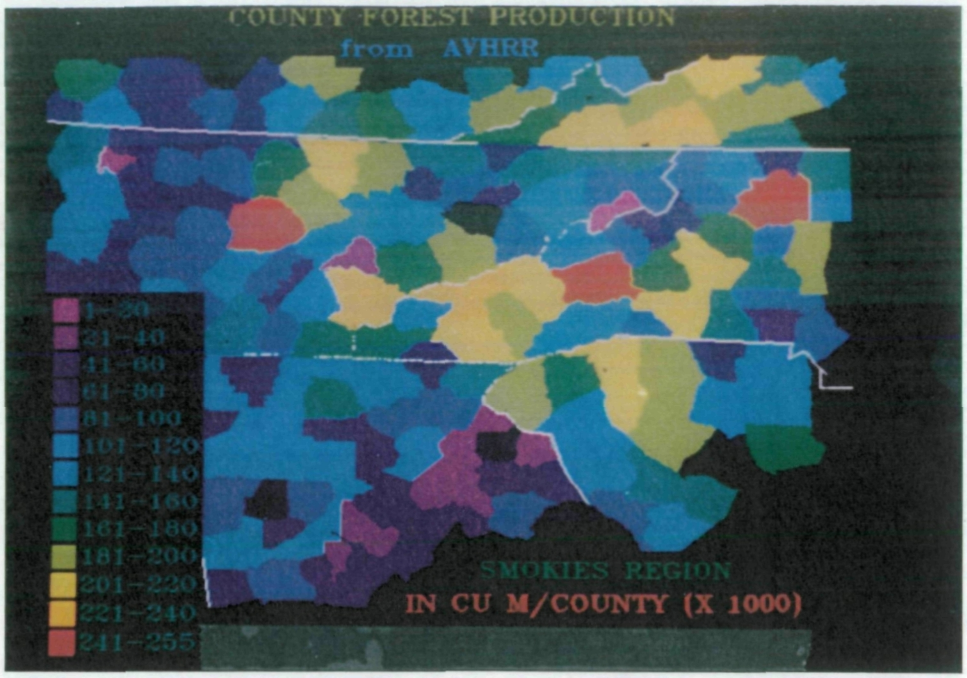

Fig. 30. County productivity for the Illinois Smokies region as ascertained from aggregation of AVHRR pixels in Fig. 29.

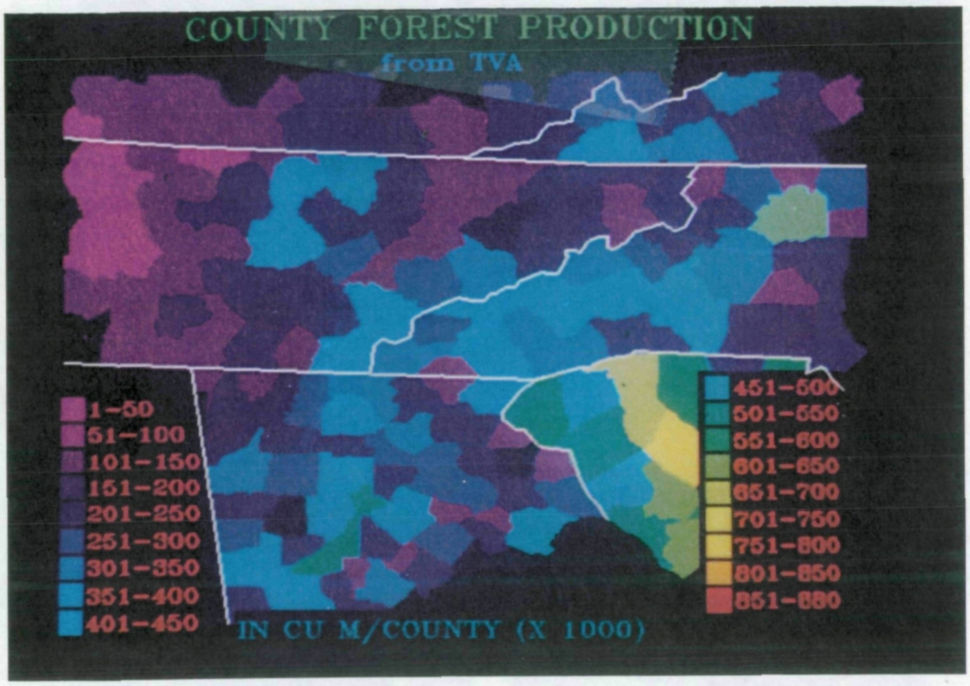

Fig. 31. County forest productivity for the Smokies region as estimated by the USFS.

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Table 19. Smokies Productivity as predicted by AVHRR correlations to TVA estimates of total, hardwood, and softwood annual growth increments.

a. Over all counties — Correlation of AVHRR estimated productivity to:

	Total Forest		Hardwood Forest		Softwood Forest		
Category	r	P	r	P	r	P	N
All	.52	.0001	.62	.0001	.87	.0001	168
By Buffer							
0-100 km	.86	.0001	.78	.0001	.52	.0074	27
100-200	.55	.0001	.75	.0001	.80	.0001	91
200-300	.47	.0001	.58	.0001	.94	.0001	64
By State							
GA	.72	.0001	.80	.0001	.90	.0001	49
KY	.76	.0001	.96	.0001	.54	.0173	19
NC	.78	.0001	.91	.0001	.48	.0065	32
SC	.55	.0228	.62	.0076	.29	.2618	17
TN	.73	.0001	.85	.0001	.80	.0001	55
VA	.66	.0134	.88	.0001	-.23	.4965	13

b. Hardwood >40% of forest

All	.68	.0001	.91	.0001	.53	.0001	78
By Buffer							
0-100 km	.78	.0004	.88	.0001	.47	.0641	16
100-200	.64	.0001	.90	.0001	.59	.0001	45
200-300	.77	.0008	.94	.0001	.27	.3730	15
By State							
GA	.86	.0013	.88	.0008	.84	.0022	10
KY	.79	.0021	.92	.0001	.27	.3912	12
NC	.82	.0001	.93	.0001	.36	.1663	17
TN	.74	.0001	.96	.0001	.82	.0001	29
VA	.75	.0119	.99	.0001	-.26	.539	10

c. Mountains occupying >50% of county

All	.63	.0001	.89	.0001	.52	.0001	70
By Buffer							
0-100 km	.78	.0004	.88	.0001	.47	.0641	16
100-200	.61	.0001	.88	.0001	.58	.0002	42
200-300	.68	.0319	.94	.0001	.28	.4282	10
By State							
GA	.87	.0022	.88	.0018	.84	.0047	9
KY	.80	.0092	.95	.0001	.08	.8414	9
NC	.82	.0001	.93	.0001	.36	.1663	16
TN	.69	.0001	.95	.0001	.82	.0001	25
VA	.75	.0119	.99	.0001	-.26	.5385	10

between the two estimates. Correlations with hardwood production among states was even better, ranging from 0.62 in South Carolina to 0.96 in Kentucky (Table 16).

Further evidence for a good potential in estimating, especially hardwood production, can be found in Table 18b, where only counties >40 percent hardwood forest are considered. Here, the overall correlation to hardwood production was 0.91, with state correlations ranging from 0.88 to 0.99 (all highly significant but sample sizes were small). Enhancement of correlation coefficients also occurred when a subset of data was made which included only those counties with greater than 50 percent mountains (Table 18c).

Evaluations by buffer distance revealed a correlation of 0.86 within 100 km, falling to 0.47 at the 200 to 300 km distance (Table 18a). The trend was similar, but more drastic, in percent forest estimates for the Smoky Mountains (Table 16a). As one would logically predict, the relationship is best in the vicinity of the calibration center; however, with production, the relationship remains significant across the entire scene among the distances and subsets tested (Table 18).

c. *Comparisons Among Sites*

The overall correlation between estimates (AVHRR vs. USFS) of annual forest production was 0.72 for the Illinois region and 0.52 for the Smoky Mountain region. The fit was generally better for the Illinois region, probably for the same reasons discussed earlier--more level topography, more homogenous landscapes, and more consistent dominance of hardwood forest types.

V. CLASSIFICATION STUDIES METHODS

A. Study Site

A study area in the Colorado Rocky Mountain Front Range, enclosed entirely within the Ward, Colorado, 7.5 minute quadrangle (Fig. 32), was chosen to study vegetation distributions in the alpine to montane plant zones. The area surrounding Niwot Ridge, a long-term ecological research site (LTER) for alpine tundra and located along the east side of the Continental Divide approximately 50 km west of Boulder, Colorado, was selected for study because ecological surveys and vegetation maps exist for this area (Keammerer, 1976; Komarkova and Webber, 1978; Hansen-Bristow, 1981), and earlier remote sensing studies were conducted here (Frank and Thorn, 1985; Frank and Isard, 1986). This area contains a diversity of vegetation types within a relatively small area for three primary groups--alpine, subalpine and montane ecosystems (Table 19).

1. Alpine Ecosystems

Niwot Ridge slopes gently to the east, dropping from 3,750 to 3,400 m above sea level (asl). Strong prevailing winds from the west control the distribution of snow cover, producing windswept knolls and areas of deep snowpack. West-facing slopes and ridge tops are generally free of snow due to wind action, while east slopes usually accumulate snowpack. Vegetation exhibits a general change from moist communities in the west to drier communities in the east (Komarkova and Webber, 1978). Local controls on vegetation are influenced by local habitat characteristics, particularly soil moisture, snow accumulation, and soil disturbance (Webber and May, 1977). In turn,

Table 19. Description of dominant vegetation ecosystems in the Colorado Rocky Mountain Front Range (Hansen-Bristow, 1981; personal communication, 1987).

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1. Wet herbaceous meadow (sedge-elephantella). This ecosystem consists of herbaceous species which form dense cover found below timberline on both steep slopes (along a drainage or below areas of late lying snow) and on flat or gently sloping sites of poor drainage.

2. Dry herbaceous meadow (golden banner-yarrow). This ecosystem forms an open to dense community found below timberline on both gentle and steep slopes with good drainage and low soil moisture.

3. Moist alpine meadow (alpine avens alpine meadow). A low herbaceous ecosystem found on moist, leeward and north-facing slopes, forming a dense, tight turf, generally with less than 25 percent-exposed rock.

4. Kobresia alpine meadow (Kobresia myosuroides). This alpine ecosystem consists of small dense clumps of this sedge species. It is covered during winter with only scattered snowbanks which melt early in the spring. This ecosystem is found on the mesic end of the moisture gradient, and is found mostly on well-drained interfluves and broad ridges.

5. Dry sedge-Kobresia alpine meadow (Carex-Kobresia). This is a rocky ecosystem composed of low grass species found in areas of good soil drainage and sparse winter snow cover, often on ridge tops or on well stabilized talus slopes.

6. Moss campion-rocky alpine meadow (Silene acaulis-Carex rupestris). Highly tolerant ecosystem found only on extreme wind-exposed ridges, with ground surface cover 50 to 80 percent rock.

7. Salix bog (Sphagnum-Salix-Betula). A dense, very moist, broad-leaved deciduous shrub and moss ecosystem found in areas of excessive soil moisture below timberline.

8. Salix moist meadow (Salix). An open to semi-dense broad-leaved deciduous shrub found in areas of mesic soil moisture below timberline, where snow cover does not last long into the growing season.

9. Krummholz (Picea-Abies-Pinus). Low, open krummholz interspersed with alpine meadows located where winter snow protects krummholz islands from dessicating winds. Distribution results from strong westerly winds moving downslope, over the alpine and into the forestlpine tundra ecotone.

10. Flag-tree (Picea-Abies-Pinus). Low to medium tall open forest. Trees are flagged, supporting branches on only the leeward side of the main stem. Located within the lower zone of the forest-alpine tundra ecotone, the ecosystem lies immediately above timberline.

11. Picea engelmannii-Abies lasiocarpa (engelmann spruce-subalpine fir forest). A stable needle-leaved evergreen forest. Located within the upper zone of the forest, this ecosystem grades at lower elevations into the ponderosa pine and lodgepole pine forests and at higher elevations into the alpine zone. This is a climax forest, found in undisturbed areas, with small islands of flag trees, dry golden banner-yarrow meadows, wet sedge-elephantella meadows, rock outcrops, lodgepole pine, limber pine, and peat moss communities.

12. Pinus flexilis (limber pine forest). This open, needle-leaved evergreen forest ecosystem is found on wind-swept, dry, rocky ridges where little competition from other species exists. The ecosystem is drought-tolerant and forms the uppermost treeline on windy ridges.

13. Populus tremuloides (quaking aspen forest). The aspen ecosystem is an open to dense, broad-leaved deciduous forest. The ecosystem ranges in elevation throughout the entire forest of the study area, and even extends to treeline on a south-east facing slope of Niwot Ridge. It is found on both wet and dry slopes. This community has variable ecotypes ranging from moist to mesic to dry soil conditions.

14. Pinus contorta (lodgepole pine forest). This ecosystem is a dense, successional, narrow-trunk, needle-leaved evergreen forest. This ecosystem seldom occurs below 2,560 m, and if lower, is usually restricted to mesic, north-facing slopes. It is found rarely at treeline and within the forest-alpine meadow ecotone, and is most frequently found below timberline, in dry soils.

15. Pinus ponderosa (ponderosa pine forest). This ecosystem is an open, needle-leaved evergreen forest that is found only within the lower elevations of the study area, mainly on south-facing slopes. This ecosystem is a topographic climax on hot and dry slopes, a topoedaphic climax on deep soils on the lower part of the south-facing slopes, and a edaphic climax on very coarse soils on north exposures and ridgetops (Marr, 1961).

16. Pseudotsuga menziesii (Douglas-fir forest). The Douglas-fir ecosystem is a fairly dense needle-leaved evergreen found mainly on north-facing slopes in moist canyons. Within the higher elevations, this community is located on the more mesic sites, and within the lower elevations it is found on steep, north-facing slopes. It is not abundant in the study area.

these factors are controlled by the interaction of slope and aspect. Above the timberline, no trees are found, rather deep-rooted mat and cushion plants, dwarf willows, grasses, and sedges. Grassy slopes are usually referred to as alpine meadows to distinguish them from the more rocky fellfields (Weber, 1976).

2. Subalpine Ecosystems

The forest-alpine tundra, ecotone surrounds Niwot Ridge in a subalpine zone approximately 3,400 to 2,700 m asl. Vegetation is characterized by a mosaic of _Picea engelmannii_, _Abies lasiocarpa_, and _Pinus flexilis_, moist meadows, ponds, and bogs. The zone represents transitional vegetation types between the alpine and montane forests.

3. Montane Forests

Forest ecosystems are found in the montane zone from approximately 2,700 to 2,500 m asl. This zone is transitional between the subalpine zone above and the foothill vegetation types below. Dominant forest ecosystems are _Pinus contorta_, _Picea engelmannii_ and _P. pungens_, _Pseudotsuga menziesii_, _Populus tremuloides_, and some _Pinus ponderosa_ (Weber, 1976).

Structural characteristics and habitat descriptions of the alpine, subalpine, and montane ecosystems that were used in this study were summarized for each ecosystem (Hansen-Bristow, 1981; personal communication, 1987) (Table 19).

1. _Alpine vegetation_: (1) wet herbaceous meadow (sedge-lephantella), (2) dry herbaceous meadow (golden banner-yarrow), (3) moist alpine meadow (alpine avens alpine meadow), (4) _Kobresia_

alpine meadow (dry), (5) dry sedge-*Kobresia* alpine meadow, and (6) moss campion-rocky alpine meadow (fellfield).

2. *Subalpine vegetation*: (7) *Salix* bog, (8) *Salix* moist meadow, (9) krummholz (conifers in upper portion of ecotone), (10) flag-trees (in lower portion of ecotone), (11) *Picea engelmannii* and *Abies lasiocarpa*, and (12) *Pinus flexilis*.

3. *Montane vegetation*: (13) *Populus tremuloides*, (14) *Pinus contorta*, (15) *Pinus ponderosa*, and (16) *Pseudotsuga menziesii*.

B. Classification Procedure

A map of dominant vegetation ecosystems (Table 19) covering the Ward, Colorado, 7.5 minute quadrangle (Fig. 32), prepared by Hansen-Bristow (1981), was digitized from the 1:24,000 scale sheet, and subsequently converted into raster format with 30 m x 30 m resolution. The area surrounding Niwot Ridge was extracted for the study area enclosed within a rectangle defined by Universal Transverse Mercator coordinates: 447000E to 457000E and 4437000N to 443000N (Fig. 33).

1. Landsat TM Transformations

A Landsat-5 TM digital image acquired on June 29, 1984, was geographically referenced to the study area represented by the map (Graham, 1977). Landsat TM data were acquired for seven spectral bands: TM1 (.45-.52fm), TM2 (.52-.60fm), TM3 (.63-.69fm), TM4 (.76-.90fm), TM5 (1.55-1.75fm), TM6 (10.40-12.48fm), and TM7 (2.08- 2.35fm). TM7 was found to be highly correlated (r=0.98) with TM5, and along with the thermal band (TM6), was not used in this study. The TM spectral bands were transformed into five band ratios and normalized difference

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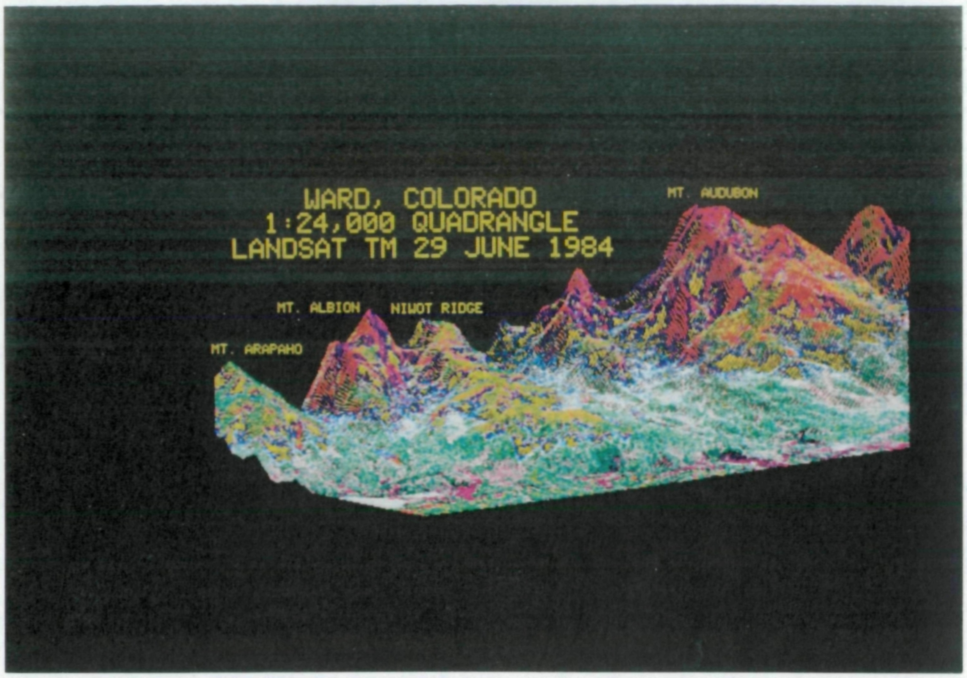

Fig. 32. Ward Quadrangle, Boulder County, CO classified TM map as draped over DEM topographic data.

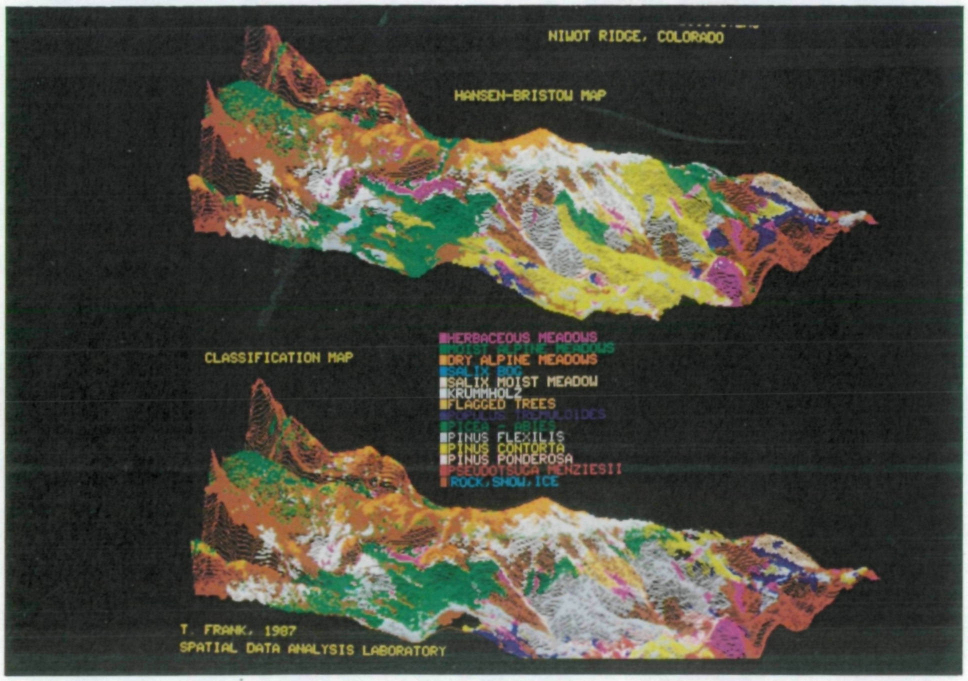

Fig. 33. Three dimensional presentations of GIS vegetation map of Niwot Ridge (top) and classification map of same based on TM and DEM data (bottom).

variables to characterize the spectral patterns of vegetation ecosystem cover types:

1. Vegetation Index Ratio of NIR and RED bands

   VI1 = TM4/TM3*(S.D.TM4+S.D.TM3) (4)

2. Normalized difference with NIR and RED bands

   ND1 = ((TM4-TM3)/(TM4+TM3) + 1.) / 2. * K (5)

3. Vegetation Index Ratio of NIR and MIR bands

   VI2 = TM4/TM5 * (S.D.TM4+S.D.TM5) (6)

4. Normalized difference with NIR and MIR bands

   ND2 = ((TM4-TM5)/(TM4+TM5) + 1.) / 2. * K (7)

5. Reflectance/absorptance ratio R/A = TM4/(TM3+TM5)

   * (S.D.TM4+((SD.TM3+S.D.TM5)/2.)) (8)

where: k is constant used to convert to eight-bit integer

S.D. is standard deviation

Band ratios and transformations were used to reduce differences between illuminated and shadowed slopes, and to enhance the spectral absorption and reflectance differences of vegetation ecosystems.

2. Topographic Measures Derived From DEM

Topographic effects on vegetation distributions were examined using estimates of elevation, slope, aspect, and relief to characterize vegetation ecosystem types in this study area. Digital Elevation Model (DEM) data came directly from the Ward, Colorado, DEM prepared by the United States Geological Survey. The DEM contains elevation data in a UTM referenced matrix for 30 m x 30 m elements (Elassal and Caruso, 1983). Slope gradient was calculated from the partial derivatives in the east-west and north-south directions of the

study area. Slope was then measured as the magnitude of the elevation gradient:

$$\text{Slope} = \text{SQRT}((ef/ex)^{**}2 + (ef/ey)^{**}2) \quad (9)$$

where: $ef/ex=(8f(x+h)-8f(x-h)+f(x-2h)-f(x+2h))/12h$

$ef/ey=(8f(y+h)-8f(y-h)+f(y-2h)-f(y+2h))/12h$

where: ef/ex is the partial derivative in the east-west

ef/ey is the partial derivative in the north-south

h is the grid interval in meters

Aspect, the direction of slope, was calculated from the two partial derivatives:

$$\text{Aspect} = \arctan((ef/ey)/(ef/ex)) \quad (10)$$

This method has been shown to approximate the true slopes and aspects in a digital elevation model (Snyder, 1983). Elevation was used to represent the altitudinal gradient of vegetation ecosystems, and aspect was used to approximate differences in exposure to solar radiation. Elevation and aspect have been used widely to characterize vegetation distributions (Hoffer, et al., 1975; Strahler et al., 1978; Hutchinson, 1982; Frank and Thorn, 1985; Cibula and Nyquist, 1987)

Local differences in elevation which create convex or concave slopes also characterize moisture gradients in mountain vegetation. Measures such as relief, the absolute difference between the highest elevation in the study area and the elevation at a specific location in the study area, can represent landscape drainage characteristics. In this study, local relief was used to measure variations in elevation from a general trend in the altitudinal gradient. This measure was used to characterize favorable habitats for dry or wet vegetation types. The altitudinal gradient was approximated by a

polynomial function derived from the digital elevation model. Predicted elevation was a function of x,y map coordinates using a third order polynomial. Then local relief was the difference between actual elevation and predicted elevation:

$$\text{Relief} = \text{Elevation} - (a0 - a1X + a2Y + a3X2 + a4XY + a5Y2) \quad (11)$$

where: X and Y are DEM Cartesian coordinates

Elevation is from the DEM

This method accounts for any general tendency in altitudinal gradient in both the east-west and north-south directions simultaneously. Consequently, the local relief is calculated for a particular study site so that the measure is sensitive to local differences that may be associated with vegetation habitats.

3. Topoclimatic Index Derived From DEM

A topoclimatic index was created from the digital elevation model to distinguish between favorable habitats for windblown, xeric ecosystems and snow-covered, mesic ecosystems. Slope-aspect index (SAI) was used in this study to characterize prevailing wind effects on soil moisture and subsequent vegetation distributions:

$$\text{SAI} = \sin(\text{slope}) * \text{aspect} / \text{max.SAI} * K \quad (12)$$

where: max.SAI is maximum index value

K is constant to convert to eight bit value

Topoclimatic conditions were defined by relationships between wind patterns and aspect and slope effects on snow accumulation for three topographic conditions:

C-2

northwest facing slopes: 270 < aspect < 360

SAI=(90.-(360.-aspect)) * sin(slope) / Max.SAI * K

northeast facing slopes: 0 < aspect < 90

SAI=(180.-(90.-aspect)) * sin(slope) / Max.SAI * K

south facing slopes: 90 < aspect < 270

SAI=(270.-aspect) * sin(slope) / Max.SAI * K

High values of SAI indicated areas that are generally leeward, steep slopes that usually accumulate deep, long-lasting snow banks. Low SAI values indicated areas that are windblown, snow-free, and generally highly dessicated. SAI was shown previously to be a good discriminator of alpine vegetation types on Niwot Ridge, even when the types did not exhibit spectral reflectance/absorptance differences (Frank and Isard, 1986). SAI was adapted for use in this study to discriminate among ecosystems in the forest-alpine tundra ecotone and the forest ecosystems.

4. Determination of Classification Variables

Samples from the dominant vegetation ecosystems were stratified by structural/plant zone grouping with reference to the Hansen-Bristow (1981) map. Spectral, topographic, and topoclimatic characteristics of the ecosystems were characterized by VI1, ND1, VI2, ND2, R/A, elevation, slope, aspect, relief, and SAI. The ability of the spectral, topographic, and topoclimatic variables to discriminate among the dominant vegetation ecosystems was examined using the statistical procedure discriminant analysis. Based on the collection of variables, the problem was to distinguish among the

vegetation ecosystems, and to identify the variables that were important for distinguishing among the groups.

Linear combinations of the predictor variables were formed from the analysis, which served to post-predict the sample memberships, and to subsequently serve as the basis for classifying new observations. Each predictor variable had a unique coefficient for each dominant vegetation ecosystem so that the original value of each variable, multiplied by the coefficient, and summed over the predictor variables, provided a discriminant score for an observation for each dominant ecosystem. Then using the discriminant scores, each observation was assigned to the dominant ecosystem using the posterior probability: the probability that an observation with a discriminant score of D belonged to dominant vegetation ecosystem group G was estimated by the conditional probability, and the observation was assigned to the group which produced the largest conditional probability.

The best predictor variables were found by calculating a discriminant function value for each observation, then calculating the correlation between each predictor variable and the discriminant function values. ND1, VI2, R/A, elevation, aspect, relief, and SAI were the best predictors of vegetation ecosystems. ND2, VI1, and slope were highly correlated with at least one other variable, and were not necessary for classification. Both topographic and topoclimatic variables were necessary, in combination with the Landsat spectral variables, to distinguish among the dominant ecosystems because no single variable exhibited sufficient difference among all ecosystems.

VI. CLASSIFICATION RESULTS AND DISCUSSION

A. Classification

The study area was stratified into three structural groups for classification. First, alpine meadow observations were assigned to one of the six dominant alpine meadow vegetation ecosystem classes using the set of predictor variables. The classification was repeated for subalpine and montane forests. Therefore, three separate classification maps were derived independently, eliminating classification error between groups. The three maps were overlayed to produce a composite map (Fig. 33). Prior to comparing the classification map to the Hansen-Bristow (1981) map, the classification map was filtered to eliminate small classification errors. This step was necessary because Landsat-derived maps exhibit spatial variability not usually evident on manually-derived maps. The degree to which this is a problem depends on (1) the level of detail expressed on the map, and subsequent pattern sizes selected for display at various scales of published maps; and (2) the spatial diversity identified within the image, controlled primarily by the resolution of the data in the image. A neighborhood filter was applied to the classification map, thereby removing some spatial diversity from the classification (Guptill, 1978).

B. Assessing Agreement Between Classification and Map

Evaluation of the classification was conducted by comparing the predicted dominant vegetation ecosystem classification against the Hansen-Bristow (1981) map. Site-specific comparisons were made by calculating the frequency of coincident classes, point by point, on the map and the classification, and reporting coincident frequencies in an error matrix (Table 20). The row sums on the right

edge of the error matrix give the total number of observations for each ecosystem from the map, and column totals along the bottom of the error matrix give the total number of observations for each ecosystem from the classification. Elements along the diagonal of the error matrix indicate the frequency of agreement between the classification and the map. For each vegetation ecosystem, percent correct, percent commission, and percent omission errors were calculated from the error matrix. These are widely used measures for assessing classifications against maps (Campbell, 1987). Overall percent agreement was averaged from the individual percent correct measures.

A better measure of overall agreement between the map and the classification was the Kappa statistic (Cohen, 1960; Bishop et al., 1975; Congalton and Mead, 1983). Kappa adjusts the overall percent correct measure by subtracting the estimated contribution of chance agreement. Kappa, the maximum likelihood estimate from the multi-nomial distribution and a measure of the actual agreement of two maps minus the chance agreement, is discussed elsewhere (Congalton and Mead, 1983).

Not all vegetation ecosystem classes could be identified with certainty, so classes were aggregated together within structural groups, but not between structural groups. The aggregation resulted in three alpine meadow classes, four subalpine classes, and seven montane classes (Table 20). The areal proportions of dominant vegetation ecosystems were then calculated for the aggregated classes from both the map and the classification (Table 21).

C. Community Classification Variations

The results of this study suggest that Landsat TM data, in combination with topographic and topoclimatic indexes, can be used

Table 20. Coincident frequency matrix and accuracy assessment for dominant vegetation ecosystems from the Hansen-Bristow (1981) map and classification results.

Classification Results

Dominant Meadow Ecosystems

Hansen-Bristow Map	1	2	3	%Corr	%Comm	%Om
Herbaceous meadows	2279	93	327	84.44	7.77	15.56
Moist alpine meadows	74	1628	753	66.31	20.16	33.69
Dry alpine meadows	118	318	2849	86.73	27.49	13.27

Kappa .6954 % Overall agreement 80.06

Dominant Subalpine Ecosystems

	4	5	6	7	8	9	%Corr	%Comm	%Om
Salix bog	109	0	1	0	0	0	99.09	30.13	0.91
Salix meadow	0	335	3	2	0	0	98.53	32.87	1.47
Krummholz	47	164	4410	430	0	0	87.31	0.09	12.69
Flagged trees	0	0	0	177	0	0	100.00	70.94	0.00
Picea-*Abies*	0	0	0	0	10448	3171	76.72	15.21	23.28
Pinus flexilis	0	0	0	0	1874	2880	60.58	52.40	39.42

Kappa .6190 % Overall agreement 76.33

Dominant Montane Ecosystems

	10	11	12	13	%Corr	%Comm	%Om
Populus tremuloides	1328	135	57	268	61.34	37.15	38.66
Pinus contorta	646	1986	656	1185	18.44	35.73	81.56
Pinus ponderosa	11	5	293	38	77.51	74.76	22.49
Pseudotsuga menziesii	3	3	51	259	75.95	86.74	24.05

Kappa .3762 % Overall agreement 55.83

Table 21. Areal coverage estimates of dominant ecosystems from map (Hansen-Bristow, 1981) and classification results.

	Map		Classification	
	Ha	%	Ha	%
Meadow Ecosystems				
Herbaceous meadows	242.91	5.50	222.39	5.10
Moist alpine meadows	220.95	5.00	183.51	4.21
Dry alpine meadows	295.65	6.69	353.61	8.11
Subalpine Ecosystems				
Salix bog	9.90	0.22	14.04	0.32
Salix moist meadow	32.85	0.74	44.91	1.03
Krummholz	457.20	10.34	397.26	9.11
Flagged trees	15.93	0.36	54.81	1.26
Picea-Abies	1241.19	62.04	947.43	47.35
Pinus flexilis	277.65	13.88	358.65	17.93
Montane Ecosystems				
Populus tremuloides	121.68	6.08	120.69	6.03
Pinus contorta	325.17	16.25	357.39	17.86
Pinus ponderosa	6.03	.30	86.94	4.35
Pseudotsuga menziesii	28.98	1.45	129.60	6.48

Kappa .6828 % Overall agreement 73.56

to map dominant vegetation ecosystems in the Colorado Rocky Mountain Front Range. Alpine, subalpine, and montane ecosystems were identifiable when compared to a manually-derived vegetation map.

Herbaceous meadows (84.44 percent), moist alpine meadows (66.31 percent), and dry alpine meadows (86.73 percent) compared favorably with the map, and errors of commission and omission were not a significant problem. However, fellfield ecosystems were not distinguishable from dry alpine meadows because spectral and topographic differences were not sufficiently different at the resolution of the data base. Wet alpine meadows were not distinguishable from wet herbaceous meadows because the spectral characteristics of wet ecosystems were similar, even though elevation differences existed between the ecosystems.

Six subalpine ecosystems could be mapped accurately; however, flagged-trees and Pinus flexilis had high errors of commission. Flagged-trees were predominantly a structural difference among Picea, Abies, and Pinus ecosystems, therefore, high errors of commission were not unexpected. Pinus flexilis did not occur frequently in the study area, and spectral differences were not apparent between this ecosystem and Picea engelmannii and Abies lasiocarpa.

Four montane forest ecosystems were difficult to map. A deciduous-coniferous distinction was obvious, yet each ecosystem had unique problems. Populus tremuloides was not confused often with other forest ecosystems, but then it was only correctly identified 61.34 percent of the time. Pinus contorta was identified poorly (18.44 percent correct) due to high errors of omission (81.56 percent). Pinus ponderosa was the most distinguishable forest ecosystem (77.51 percent correct), but this ecosystem had a high error of commission (74.76 percent). Pseudotsuga menziesii also had a high correct

classification (75.95 percent) and a high error of commission (86.74 percent).

Areal comparisons between ecosystems estimated from the classification and the map (Table 21) indicated that alpine meadow ecosystems compare favorably overall; subalpine ecosystems compare favorably with the exception of Picea-Abies and Pinus flexilis; and montane forest ecosystems do not compare favorably, even though Populus tremuloides and Pinus contorta appear to have approximately similar distributions. The two distributions do not coincide spatially (Table 20).

The results of this study suggest that Landsat TM, in combination with topographic and topoclimatic indexes, may be useful to map some dominant vegetation ecosystems in the Colorado Rocky Mountain Front Range. Alpine meadow and subalpine ecosystems were identified more accurately than expected, using the spatial resolution of Landsat TM and USGS digital elevation data. Results for meadow and subalpine ecosystems suggest that the models used in this study should be useful for mapping other alpine and subalpine ecosystems in the Front Range. However, the poor results for forest ecosystems suggest that additional procedures must be developed to better delineate various forest ecosystems in mountainous environments.

Preliminary efforts have been made in this study to develop a new approach in examining the topographic vegetation distribution model. The approach involves calculating a statistical description of the vegetation distribution along elevational and slope-aspect gradients. A similar method was used by Fleming and Hoffer (1979), only they used field-plot data in defining their vegetation zones, whereas this effort used DEM and TM-classified data in a GIS.

The histograms shown in Figure 34 show the vegetation cover as a function of elevation, with north-facing slopes displayed on the left and south-facing slopes on the right sides of the histograms. The diagrams show the forest systems differing elevationally from the alpine meadow ecosystems, but not much differentiation among forest classes (Fig. 34). Further studies are under way to enhance the capability of separating forest classes in mountainous terrain, with the combination of topographic and spectral data in the classification process.

VII. OVERALL CONCLUSIONS

We have seen reasonably accurate regional estimates of cover and productivity with the use of TM-calibrated AVHRR data. Higher local (TM scale) variance reduces reliability of determining productivity at the individual pixel level, but when spatially averaged over the larger AVHRR pixels, spatial variance is substantially reduced.

Throughout our research it was apparent that landscape heterogeneity and structure had a strong influence on the success of our approach. We were most successful in the Illinois region where the forests are uniformly dominated by hardwoods, the topography is fairly consistent, and bodies of water are not a prominent feature of the landscape. These three features allowed consistent across-region interpretation of the TM and AVHRR spectral imagery, even though forest is not the dominant vegetation cover type of this region.

We were also generally more successful in predicting regional percent forest cover than productivity. This is reasonable to expect since one less level of scale-up was used in determining forest cover. With productivity, we went from ground points to TM scale to AVHRR scale, whereas percent forest only went from TM to AVHRR scales.

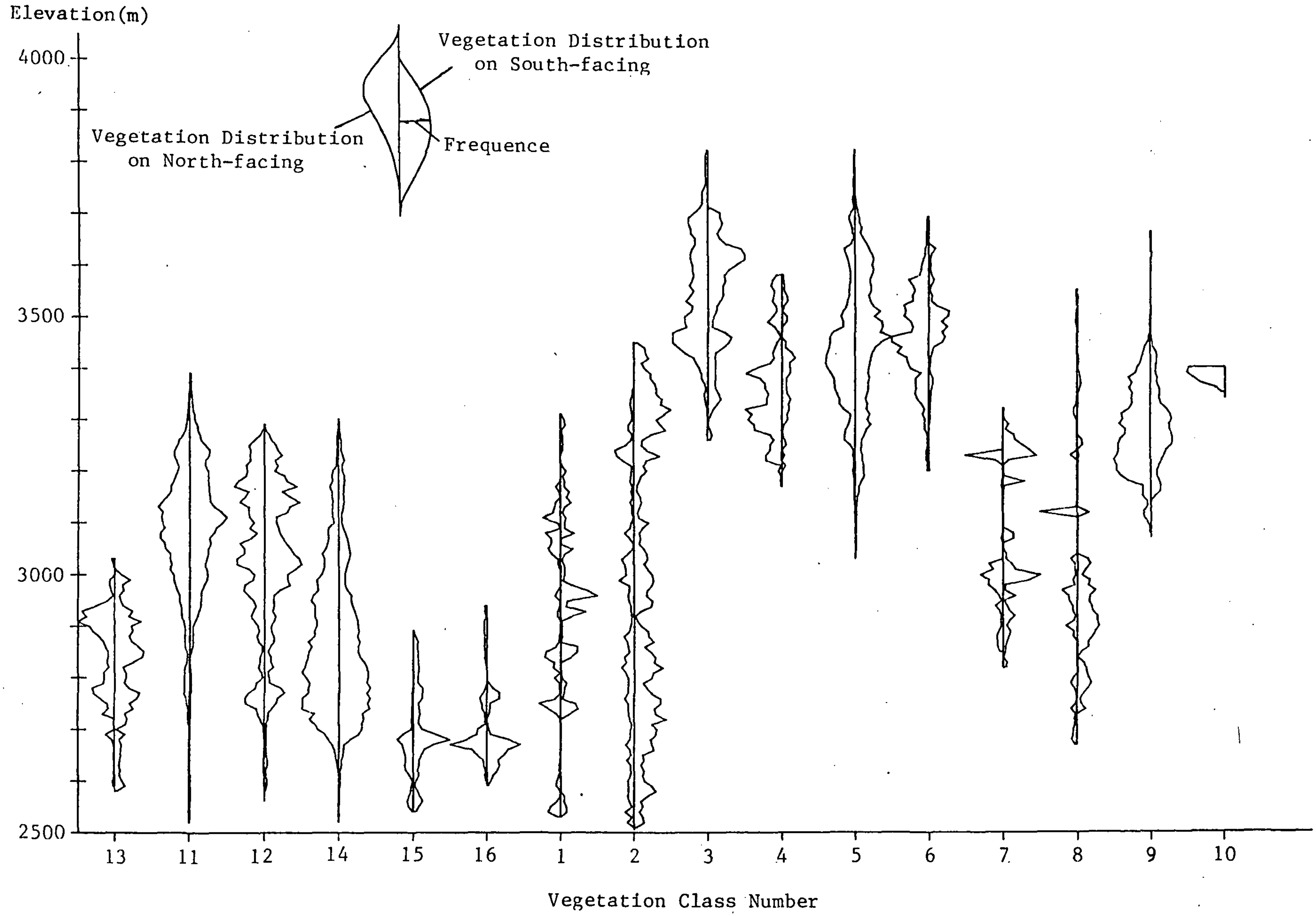

Fig. 35. Vegetation-slope-elevation diagrams for 16 vegetation classes found in Boulder County watershed (vegetation class number corresponds to classes in Table 20).

We were less successful in predicting productivity or cover in the Smoky Mountain region where the forests may be dominated by either hardwoods or conifers, the topography ranges from the mountainous region of the Smoky Mountains to flatlands of western Tennessee, and bodies of water, while frequent, are also large. The models predicted highly correlated values (r=>0.84) of production or cover within 100 km of the calibration center, but the relationships broke down outside that buffer distance. Beyond that distance, one sees the greatest change in topography and hardwood/conifer distribution. The TM/FOREST and AVHRR/FOREST models used to calibrate the Smoky Mountain AVHRR models were developed in a landscape that is dominated by hardwood. Consequently, when the forest is dominated by conifers, which have very different reflective properties, such as in the Piedmont region of Georgia and South Carolina, and the models are poor predictors of especially percent forest. Topography was influential because the TM/FOREST model was based, in part, on elevational differences in temperature, which were both captured by the TM sensor and strongly correlated with productivity in that mountainous landscape. Consequently, when topography flattened, the relationship tended to weaken.

In future work, difficulties created by conifer-hardwood contrasts and topography might also be circumvented somewhat by stratification techniques. Conifer- and hardwood-dominated pixels might be delineated by their reflectance signatures, especially in the winter. Separate TM/FOREST and AVHRR/FOREST models might then be developed for each vegetation type. Such a strategy is clearly feasible using multi-temporal TM and AVHRR scenes, at least in the Smoky Mountains where conifer and hardwood stands tend to be fairly pure. Where mixtures of hardwood/conifer stands exist within even a TM-sized pixel, the models will become more confounded.

Dividing the continents into ecologically meaningful strata, such as the "Ecoregion-continuum" regions proposed by Logan (1985), and exemplified by Bailey's ecoregions of North America (1981), provides a logical start to stratification and determination of the number of locations of calibration centers. In relatively homogenous regions (like Illinois), fewer calibration centers will be needed, whereas heterogenous areas, like the Smoky Mountains, will need a higher density of calibration centers. A GIS could be used to stratify the major regions, and one might then explore province-specific calibration models.

In the New York area, we were less successful in developing TM/FOREST models than in the other regions, and we had no success in developing AVHRR/FOREST models. This is apparently a consequence of two factors: (1) the presence of mixed hardwood-conifer stands, and (2) the presence of many small wetlands and lakes. The mixed conifer-hardwood stands created difficulties in finding TM characteristics that were uniformly related to forest productivity. We were successful in developing TM/FOREST models only if we stratified the data based on forest type. In the larger AVHRR pixels, the signature was confounded by not only the extreme heterogeneity of the forests but also the wetland component of the landscape. Here again stratification of the region might improve one's ability to extend ground-based data to regional estimates.

In the subalpine Rockies, the spatial pattern of the vegetation was too fine to be captured with TM data without the addition of biogeographical data such as slope, aspect, and elevation. We made no attempt to create AVHRR/FOREST models in this region because the fine-scale spatial heterogeneity and the lack of suitable productivity measurements precluded using our approach. However, the methods employed in this study did greatly increase the classification accuracy over the

use of TM data alone. Differentiation of such community types will be valuable in pursuing this line of research.

In summary, our approach of using nested scales of imagery in conjunction with ground-based data and a geographic information system can be very successful in generating landscape and regional estimates of variables which cannot be directly measured by a sensor but are functionally related to some variable a sensor can detect. Furthermore, the approach permits the error associated with such estimates to be documented and is extremely thrifty in its use of imagery. The approach will be most useful in regions where either the functional relationship is not confounded by other features of the landscape or the confounding landscape features can be stratified to reduce the overall variance. Our research is a prototype of the research that will be needed to develop spatially-extensive estimates with quantifiable accuracy of those globally important variables that cannot be measured directly from satellite sensors. As new sensors are developed, many more important biosphere variables will become possible to indirectly sense through their relationship to variables that can be sensed directly. Our ability to detect global processes and map global patterns will depend on our ability to capitalize on these relationships.

Among the many challenges in developing regional and global models is quantifying the accuracy of those models. Our experience suggests that techniques for extending limited ground-based data to much larger regions should be developed where they can be rigorously tested, even though the techniques are most needed in regions of the globe where imagery is the only source of extensive data. We believe that in our current stage of model and sensor development, it is only prudent to work in regions of the

globe where the models or modeling approach can be validated through comparison with independent data.

Our research experience working with very different landscapes supports the argument for much more work on stratification techniques and evaluating heterogeneity within strata. What causes heterogeneity within a strata, and what is the spatial resolution of that heterogeneity? Can one use analysis of variance in a rigorous sense to test the goodness of the stratification? How does landscape affect our ability to stratify? Answering these questions will require that we map features of a landscape or region, i.e., describe the pattern, independently of knowledge of the processes that created those patterns. The potential is there and the possible yield is great. If a network of calibration centers via stratification is accomplished, repeated forest productivity or cover estimates can be performed relatively easy using newly acquired AVHRR data. In this way, we can monitor global vegetation change and perhaps provide tools for developing public policy to better manage our global biospheric and atmospheric resources. It is our responsibility to do no less.

VIII. BIBLIOGRAPHY

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X. APPENDIX

A. Extensive Site Preliminary Studies

In addition to the four intensive sites reported on here, preliminary data collection and image processing was accomplished for a number of counties where additional study sites are located, as shown in Figure A1. This work was reported in earlier progress reports (Iverson et al., 1986a, 1986b, 1987) and will not be repeated here. The sites cover a variety of biome types, and are intended to assist in AVHRR scale-up calibration and testing. Forest growth and cover characteristics (Table A1) and climate characteristics (Table A2) also vary widely in order to cross-check AVHRR scale-up across a large diversity of landscape and biomes.

B. Facilities and Equipment

The Illinois Natural History Survey, the University of Illinois Spatial Data Analysis Laboratory (Department of Geography), and the Oak Ridge National Laboratory were the three institutions with the chief responsibility for the project. Each of these institutions have extensive computer hardware and software for image processing, GIS, and statistical analysis. Only the equipment actually used and/or acquired specifically for this project are discussed in this section.

1. Illinois Natural History Survey

The Illinois Natural History Survey has been using GIS technology in natural resources research since 1983, when the Illinois GIS began with ARC/INFO running on a Prime 750 minicomputer as the primary software and hardware. During the time-frame of the project, a Prime 9955

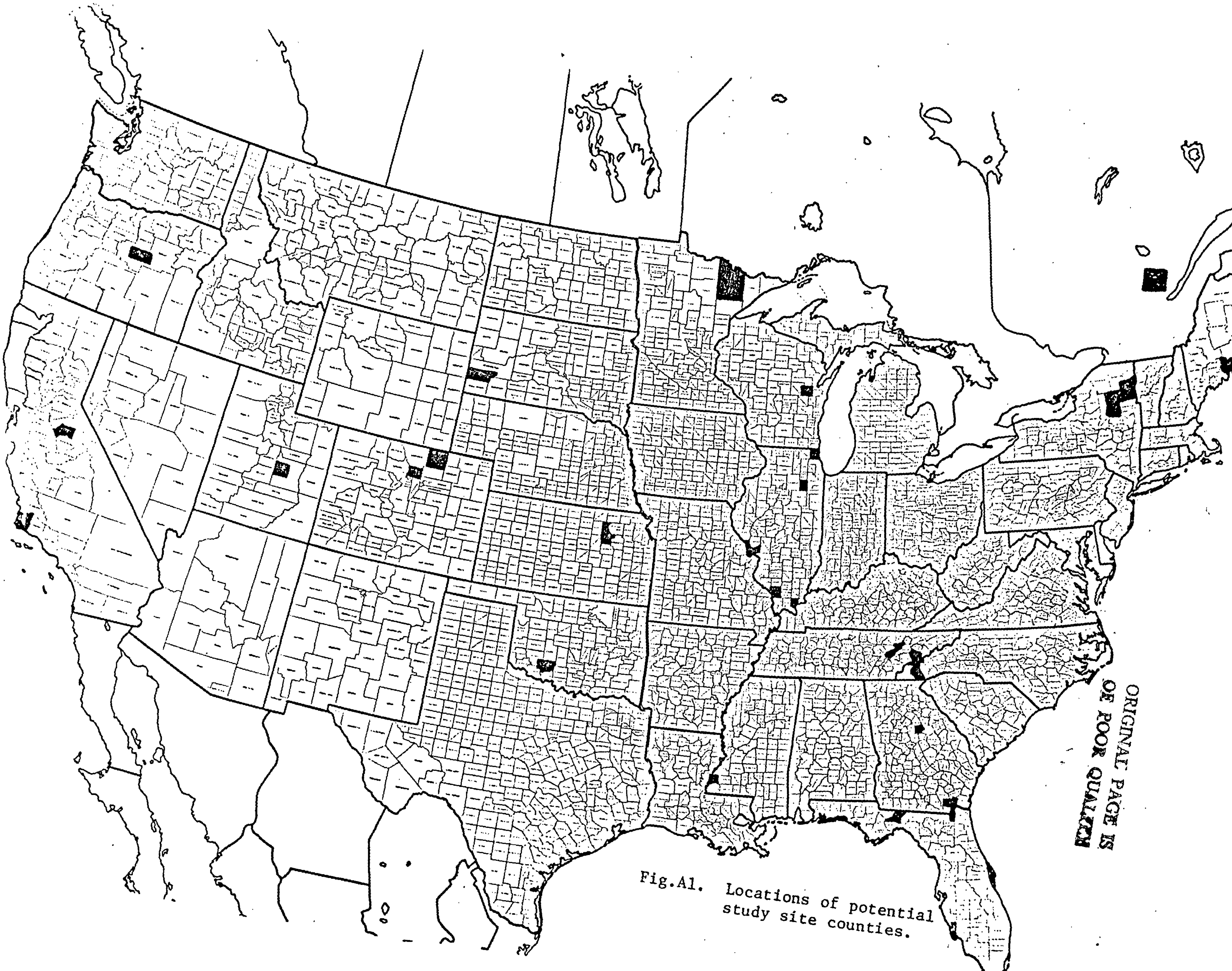

Fig.A1. Locations of potential study site counties.

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Table A1. Total, hardwood, and softwood annual growth estimates for extensive site network sites.

State	County	Commercial	Annual Growth, cubic meter/county Hardwood	Softwood	Percent forest
CA	Fresno	NA	NA	NA	1.3
CA	Tuolumne	NA	NA	NA	13.7
FL	Leon	444,600	130,300	314,300	66.6
IL	Calhoun	39,600	39,600	0	36.1
IL	Grundy	8,500	8,500	0	4.1
IL	Jackson	19,800	19,800	0	33.8
IL	Lake	8,500	8,500	0	4.3
IL	Pope	90,600	84,900	5,700	57.2
ME	Knox	158,600	39,600	118,900	70.1
ME	Waldo	354,000	90,600	263,300	76.1
MN	Itasca	962,700	475,700	487,000	76.0
MN	St. Louis	1,718,800	843,800	875,000	63.2
MS	Adams	342,600	263,300	79,300	62.2
NY	Essex	NA	NA	NA	50.4
NC	Macon	379,400	322,800	56,600	79.7
NC	Swain	147,200	110,400	36,800	31.8
OR	Crook	NA	NA	NA	22.3
OR	Grant	NA	NA	NA	52.8
SD	Custer	288,800	2,800	286,000	41.2
TN	Anderson	144,400	107,600	36,800	64.3
TN	Blount	206,700	113,300	93,400	33.6
TN	Sevier	198,200	119,000	79,300	41.1
WI	Outagamie	NA	NA	NA	17.0

The following counties had no forest information in the Geoecology data base: Boulder and Weld, CO, Geary and Riley, KS, Emery, UT.

Table A2. Some climatic characteristics of extensive site network. Source Geoecology data base.

State	County	Average Jan	Temperature, July	°C Annual	Annual Precip., cm	Annual Evapor., cm	Annual Mois.Indx.
FL	Leon	11.4	27.1	19.7	150.60	104.34	44
IL	Calhoun	- 1.7	24.8	12.2	98.76	75.67	31
IL	Grundy	- 4.5	23.3	10.3	85.34	70.08	21
IL	Jackson	1.0	25.6	13.9	110.92	80.70	37
IL	Lake	- 5.5	22.2	9.0	83.34	65.48	27
KS	Geary	- 1.8	26.0	12.7	85.14	78.69	8
KS	Riley	- 1.8	26.2	12.8	84.02	79.22	6
ME	Knox	- 5.4	19.6	7.3	115.77	58.60	98
ME	Waldo	- 6.6	20.0	7.0	105.84	59.11	79
MN	Itasca	-14.3	19.7	4.0	66.67	57.18	17
MN	St. Louis	-14.0	19.5	3.9	71.34	56.44	26
MS	Adams	9.6	27.6	19.0	139.32	101.42	37
NC	Macon	3.6	22.2	12.9	165.30	72.49	128
NC	Swain	3.4	23.0	13.2	143.43	74.40	93
NY	Essex	- 9.6	19.0	5.5	95.05	56.13	69
SD	Custer	- 4.3	22.7	8.6	43.99	63.44	-31
TN	Anderson	3.5	25.1	14.5	129.41	81.05	60
TN	Blount	4.3	24.9	14.7	129.11	81.36	59
WI	Outagamie	- 8.7	21.5	7.1	75.59	62.13	22

Data not available in Geoecology for the following counties: Boulder and Weld, CO, Emery, UT, Fresno and Tuolumne, CA, and Crook and Grant, OR.

superminicomputer was networked with the 750 to accommodate tremendous growth in the use of the system. The GIS data base consists of nearly 100 parameters, including soils, vegetation, landforms, surface hydrology, infrastructure, surficial geology, and administration units for the entire State at coarse resolution, and for selected areas at higher resolution (1-4 ha). The southern Illinois intensive study site for this project is within the area of high resolution data in the Illinois GIS. Several GIS parameters were extracted for use in percent forest and forest productivity modeling work that was done (Section IV C).

The INHS acquired an IBM PC-AT and an ERDAS image processing system in January 1986. A 20-mg removable cartridge IOMEGA Bernoulli Box was added later to accommodate storage requirements for the TM, GIS, and AVHRR data. Nearly all image processing for the study was done on this system, or a comparable one at the University of Illinois Department of Geography. Transfer of data from the Illinois GIS Prime environment to ERDAS on the PC, for much of the project's duration, was accomplished via an ELAS version 415 module for converting gridded ARC/INFO files to ERDAS format. Other PC's were used for SAS statistical analysis and graphics/word processing functions.

In June 1987, a hardware/software link for running ERDAS on the Prime, with the PC as a Prime workstation, was installed. This system has allowed better integration of GIS and remotely-sensed data, the use of more powerful hardware, and an access to greater storage and file-manipulating capability. However, we have been plagued with problems in communications such that the link is not as effective as we had hoped for. The link is quite valuable, however, especially in the TM-AVHRR-Geoecology efforts.

2. University of Illinois Spatial Data Analysis Laboratory (Department of Geography)

The University of Illinois' Spatial Data Analysis Laboratory has several networked ERDAS systems. All processing for the Colorado study site was done on these systems. The 1600 bpi tape-drive peripheral to the ERDAS systems in the laboratory was used extensively for TM and GIS file transfers before the INHS had the Prime ERDAS (and thus could use the Prime tape drives). Department of Geography staff affiliated with this study made use of the University of Illinois' IBM and Cyber mainframes as needed; for example, when the digital elevation model data on tape had a buffer size too large to read on the Prime. They also developed several ERDAS modules using ERDAS programming tools that were essential to the study. They are described in section III-B of this report.

3. Oak Ridge National Laboratory

The ORNL Computer Sciences Division has several major computer systems, as well as image processing capabilities via I^2S. Data were shared between the ORNL and INHS systems, such as digital elevation model data and the Geoecology data base from which percent forest and forest growth by county for the United States were available. The Environmental Sciences Division also acquired an ARC/INFO (on Vax computer) and ERDAS PC station during the course of the project. ORNL staff also used PC- and mainframe-based SAS.

4. Global Patterns Associates

A Compaq-286 transportable microcomputer with 60-mb hard disk was also used on this project.

C. Papers, Proceedings, and Presentations (Related to NASA Contract NAS-5-28781)

Papers

Frank, T.D. 1988. Mapping dominant vegetation ecosystems in the Colorado Rocky Mountain Front Range and Landsat TM. Photogrammetric Engineering and Remote Sensing (submitted)

Graham, R.L., L.R. Iverson, E.A. Cook, and J.S. Olson. 1988. Long-term records of stand structure and growth in the Great Smoky Mountains, Tennessee. (in review)

Graham, R.L., M.G. Turner, and V.H. Dale. 1988. Changing climate and atmospheric CO_2: forest resource issues. BioScience (in preparation)

Hunsaker, C.T., R.L. Graham, C.W. Barnthouse, S.M. Bartell, R.H. Gardner, R.B. O'Neill, and G.W. Suter, II. 1988. Assessing ecological risk at a regional scale. Landscape Ecology (submitted)

Iverson, L.R. 1988. Land-use changes in Illinois, USA: the influence of landscape attributes on current and historic land use. Landscape Ecology (submitted)

O'Neill, R.V., J.R. Krummel, R.H. Gardner, G. Sugihara, B. Jackson, D.L. DeAngelis, B.T. Milne, M.G. Turner, B. Zygmunt, S. Christensen, V.H. Dale, and R.L. Graham. 1988. Indices of landscape pattern. Landscape Ecology (accepted)

Chapters

Agbu, P.A. and T.D. Frank. 1988. Quantification of the improvement in soil mapping using SPOT HRV over Landsat MSS imagery. Pages 191-197. In: The World in Space. American Society for Photogrammetry, St. Louis, Missouri. March.

Brigham, W.U., L.R. Iverson, and E.A. Cook. 1987. An overview of the Illinois Geographic Information System and selected biological applications to surface mining and reclamation. Pages 5-10. In: Proceedings of the 1987 National Symposium on Mining, Hydrology, Sedimentology, and Reclamation, (D. H. Graves, ed.), University of Kentucky, Lexington.

Cook, E.A., L.R. Iverson, and R.L. Graham. 1987. Estimating forest productivity in southern Illinois using Landsat thematic mapper data and geographic information system

analysis techniques. Pages 255-265. In: Proceedings of the 1987 American Society of Photogrammetry and Remote Sensing and American Congress on Surveying and Mapping, Technical Papers, Volume 1, Remote Sensing, Falls Church, Virginia.

Cook, E.A., L.R. Iverson, and R.L. Graham. 1987. The relationship of forest productivity to Landsat Thematic Mapper data and supplemental terrain information. Pages 43-52. In: Proceedings of Pecora XI Symposium, American Society for Photogrammetry and Remote Sensing and American Congress on Surveying and Mapping, Falls Church, Virginia.

Iverson, L.R. and P.G. Risser. 1987. Analyzing long-term vegetation change utilizing geographic information system and remotely sensed data. Advances in Space Research 7(11): 183-194.

Olson, J.S. 1986. Global and regional synthesis: needs and opportunities for a hierarchy of scales of remote sensing and modeling. Pages 9-22. In: Coupling of Ecological Studies With Remote Sensing: Potentials at Four Biosphere Reserves in the United States, (M.I. Dyer and D.A. Crossley, eds.). U.S. Man and the Biosphere Program, Washington, D.C.

Risser, P.G. and L.R. Iverson. 1988. Geographic information system for natural resource management at the state level. Pages ----. In: Our Role in Changing the Global Environment: What We Can Do About Large Scale Environmental Issues. (D.B. Botkin, M.F. Caswell, J.E. Estes, and A.A. Orio, eds.) Academic Press (in press)

Tylka, D.L. and E.A. Cook. 1986. St. Louis vegetative cover study. Pages 43-46.. In: Proceedings of Integrating Man and Nature in the Metropolitan Environment: A National Symposium on Urban Wildlife, (L. W. Adams and D. L. Leedy, eds.), National Institute for Urban Wildlife, Columbia, Maryland.

Abstracts

Cook, E.A., J.E. Gardner, J.D. Garner, and J.E. Hofmann. 1988. Analyzing home range and habitat selection of the Indiana bat using radio telemetry and GIS techniques. 1988 Annual Meeting of the Ecological Society of America, Davis, California. -- August. (Invited and submitted)

Gardner, J.E., J.E. Hofmann, J.D. Garner, and E.A. Cook. 1987. Foraging range and habitat utilization of male *Myotis sodalis* in Illinois determined by radio telemetry and computer analysis techniques. 17th Annual

North American Symposium on Bat Research, Toronto, Ontario. October 15-17.

Garner, J.D., J.E. Gardner, J. Hofmann, and E.A. Cook. 1987. Determination of home range size and roost tree selection of Indiana bats. Midwest Fish and Wildlife Conference: 200, Milwaukee, Wisconsin. December 5-9. (Poster)

Graham, R.L., L.R. Iverson, and E.A. Cook. 1986. Assessing forest productivity in the Great Smoky Mountains National Park using Thematic Mapper spectral data. Page 58. In: Proceedings of the Third Annual Acid Rain Conference for the Southern Appalacians, Gatlinburg, Tennessee. October 27-28, 1986. (H. Olem, ed.) TVA/ONRED AWR-87/15.

Graham, R.L., L.R. Iverson, and E.A. Cook. 1987. Evaluating spatial patterns of forest productivity in a disturbed, mountainous landscape using LANDSAT data and a GIS. Bulletin of the Ecological Society of America 68: 314. (Poster)

Graham, R.L., L.R. Iverson, and E.A. Cook. 1988. Long-term records of stand structure and growth in the Great Smoky Mountains, Tennessee. 1988 Annual Meeting of the Ecological Society of America, Davis, California. -- August. (accepted)

Graham, R.L., L.R. Iverson, and E.A. Cook. 1988. Stand structure and growth in the Great Smoky Mountains, Tennessee: Whittaker's stands revisited. Pages ---. In: Proceedings of the Fourteenth Annual Meeting on Scientific Research in the National Parks of the Upland Section of the Southeast Region. Gatlinburg, Tennessee. May 12-13, 1988. (in press)

Iverson, L.R. and E.A. Cook. 1986. Ecological applications of the Illinois Geographic Information System: a case study of Jackson County, Illinois. IV International Congress of Ecology: 188.

Iverson, L.R., E.A. Cook, and R.L. Graham. 1987. GIS and remote sensing as tools for detection of landscape patterns and processes. Bulletin of the Ecological Society of America 68: 330. (Invited)

Iverson, L.R., E.A. Cook, and R.L. Graham. 1988. Applications of remote sensing to forested ecosystems. 1988 Annual Meeting of the Ecological Society of America, Davis, California. -- August. (Invited and submitted)

Major Technical Memoranda

Iverson, L.R. 1987. Biospheric studies. Pages 247-256 and 397-403. In: Landsat Workshop. Laboratory for Terrestrial Physics, National Aeronautics and Space Administration, Washington, D. C.

Iverson, L.R. 1987. Interpreting forest and grassland biome productivity utilizing nested scales of image resolution and biogeographical analysis. Pages 359-396. In: 1986 Landsat Workshop, Laboratory for Terrestrial Physics, National Aeronautics and Space Administration, Washington, D.C.

Iverson, L.R., E.A. Cook, R.L. Graham, T. Frank, Y. Ke, and J. Olson. 1986, 1987. Interpreting forest and grassland biome productivity utilizing nested scales of image resolution and biogeographical analysis. Numbers 1, 2, and 3. Reports to the National Aeronautics and Space Administration, Washington, D.C.

Iverson, L.R., E.A. Cook, R.L. Graham, T. Frank, Y. Ke, and J. Olson. 1987. Assessment of forest productivity using TM and GIS data. Pages 73-78. In: 1987 LANDSAT Workshop, Laboratory for Terrestrial Physics, National Aeronautics and Space Administration, Washington, D.C.

Abstracts Not Covered Above

Graham, R.L., L.R. Iverson, and E.A. Cook. 1987. Evaluating abandoned pasture patch stability within a forest matrix using LANDSAT TM data and historic vegetation maps. International Symposium on Landscape Ecology, Munster, West Germany. July 19. (Invited)

Oral Conferences or Workshop Presentations

Frank, T.D. 1987. Comparing Landsat TM, MSS, and digitized NHAP photography for vegetation analysis. Western Great Lakes Region of American Society for Photogrammetry and Remote Sensing Fall Meeting, Urbana, Illinois. November.

Frank, T.D. 1987. Comparison of Vegetation Mapping Techniques in Arid Environments. Arid Lands Remote Sensing Conference, Arid Lands Remote Sensing Working Group, Bishop, California. March.

Frank, T.D. 1987. Third mapping on the IBM PC/AT with professional graphics capability. Remote Information Processing/Video Image Processing Workshop, Northern Illinois University, DeKalb. April.

Frank, T.D. 1988. Comparing drainage density estimates from digitally enhanced Landsat TM and color infrared aerial imagery. Arid Lands Remote Sensing Conference, Arid Lands Remote Sensing Working Group, Reno, Nevada. April.

Gardner, J.E., J.E. Hofmann, J.D. Garner, and E.A. Cook. 1987. Foraging range and habitat utilization of male Myotis sodalis in Illinois determined by radio telemetry and computer analysis techniques. 17th Annual North American Symposium on Bat Research, Toronto, Ontario. October 15-17.

Graham, R.L. 1988. Risk assessment of the landscape at regional scale. International Association of Landscape Ecologists Meeting, Albuquerque, New Mexico.

Iverson, L.R. 1985. The Illinois Geographic Information System (GIS): a tool to better manage the State's natural resources. Regional meeting of the American Society for Photogrammetry and Remote Sensing, Northern Illinois University, DeKalb. November 1.

Iverson, L.R. 1985. Natural resources information management using the Illinois Geographic Information System. Regional meeting of the Soil Conservation Society of America, Decatur, Illinois. November 7.

Iverson, L.R. 1987. Integration of ERDAS with ARC/INFO for assessment of regional forest productivity. Midwest Regional ARC/INFO User's Conference, Champaign, Illinois. October 15. (Invited)

Iverson, L.R. and E.A. Cook. 1987. Forest productivity estimates using combinations of GIS, TM, and AVHRR data. Western Great Lakes Regional Meeting of the American Society for Photogrammetry and Remote Sensing, Champaign, Illinois. November 6. (Invited)

Olson, J.S. 1986, 1987. Uncontrolled experiments. Carbon dioxide and global climatic change. Short lecture courses. Swedish University of Agricultural Sciences, Uppsala, Sweden. September 23; Chernobyl fallout and its future in Swedish forests. Institute of Ecological Botany, Uppsala University, Uppsala, Sweden. October 2; Predicting redistribution of radiocesium in Nordic forests. Lecture to Nordic Working Conference, Radioecology Department, Swedish University of Agricultural Sciences, Uppsala, Sweden. October 29; International geosphere-biosphere program: computer models and nested remote sensing of landscape complexes. Sweden. March.

Popular Press Coverage

Iverson, L.R. 1987. Can the productivity of Illinois forests be estimated from space? Pages 5-7. In: Illinois Natural History Survey Highlights of the Annual Report, 1986-1987, Department of Energy and Natural Resources, Champaign.

Iverson, L.R. and E.A. Cook. 1988. Can the productivity of forests be estimated from space? Illinois Natural History Survey Reports No. 273.

D. Meetings, Visits, and Travel (No Presentation Given)

Cook, E.A. and L.R. Iverson. 1988. Annual Convention of the ASPRS-ACSM, St. Louis, Missouri. March 14-18.

Frank, T.D. 1986. Attended American Society of Photogrammetry and Remote Sensing (ASPRS) Fall Technical Conference, Anchorage, Alaska. October.

Frank, T.D. 1986. Attended GIS User Group Workshop, Seattle, Washington. November.

Graham, R.L. 1986. Work at the Illinois Natural History Survey, Champaign. June.

Graham, R.L. 1986. Annual Meeting of the International Congress of Ecology, Syracuse, New York. August.

Graham, R.L. 1987. Work at the Illinois Natural History Survey, Champaign. June.

Graham, R.L. 1987. Attended meeting of the International ERIM Conference, Ann Arbor, Michigan. October.

Graham, R.L. 1987. Site visit and data collection at Tennessee Valley Authority, Norris. October.

Graham, R.L. 1988. Work at the Illinois Natural History Survey, Champaign. March.

Iverson, L.R. 1985. Attended the CERMA Conference on Integration of Remote Sensed Data in Geographic INformation Systems for Processing of Global Resource Information. May.

Iverson, L.R. and E.A. Cook. 1985. Attended International ERIM Conference, Ann Arbor, Michigan. October 21-24.

Iverson, L.R., J.S. Olson, Y. Ke, and T. Frank. 1985. Attended meeting of the American Society of Photogrammetry and Remote Sensing, Indianapolis,

Indiana. (Also occurring at that time was the first TM Working Group Conference.) September 8-13.

Iverson, L.R. 1985-1988. Attended meetings of the Illinois Commission on Forest Development. (Served as Chairman of the Forest Resources Analysis Committee.) December 1985-April 1988.

Iverson, L.R. 1986. Visited the North Central Experiment Station, St. Paul, Minnesota. July.

Iverson, L.R. 1987. Site visit and data collection at Custer County, South Dakota. May.

Iverson, L.R., Graham, R.L., and J.S. Olson. 1986. Site visit to Huntington Wildlife Forest, New York. August.

Olson, J.S. Attended meeting of Land Processes Research on Forests, Goddard Space Flight Center. December 17-18.

Olson, J.S. 1986. Attended workshop on Climate-Vegetation Interactions, Goddard Space Flight Center. January 27-29.

Olson, J.S. and R.L. Graham. 1986. Relocation of Whittaker-Becking-Olson plots in Great Smoky Mountains National Park. August.

Olson, J.S. 1987. Swedish results on thematic mapper and SPOT imagery. Discussed with Margharetta Ihse and others, Department of Natural Geography, Stockholm University. February 1.

Olson, J.S. 1987. Workshop on Land Use Change and the Carbon Cycle. Oak Ridge Associated Universities, Oak Ridge, Tennessee. May 25-27.

Olson, J.S. 1987. Work at the Illinois Natural History Survey (June 8-10) and NASA Ames Laboratory, Moffett Field, California. June 11-15. Plans with David Peterson, Pamela Mattson, and colleagues.

Olson, J.S. 1987. Workshop on Positive Feedback and the Carbon Cycle. Oak Ridge Associated Universities, Oak Ridge, Tennessee. June 29-July 1.

Olson, J.S. 1987. Planning with Satimage Corporation, and Swedish Land Survey, Kiruna, Sweden. August 10 and 17.

Olson, J.S. 1987. NASA Goddard Institute of Space Sciences, Columbia University, New York City, New York. October 22-23. Coordination with Inez Fung, Vivian Gornitz, and David Hansen.

Olson, J.S. 1987. Work at Illinois Natural History Survey (November 10-12); NASA Headquarters and Goddard Space Flight Center (November 13); and National Space Technology Laboratory (November 16-18).

Olson, J.S. 1987. NASA Ames Laboratory, California (December 10-11); Yosemite and Sequoia-King's Canyon Parks (December 14-17). Options for technology transfer to National Park Service.